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Unit commitment adjustments based on risk assessment

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Unit Commitment Adjustments Based on Risk Assessment

by

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A thesis submitted to the graduate faculty

in partial fulfillment of the requirements for the degree of

MASTER OF SCIENCE

Major: Electrical Engineering

Program of Study Committee:
James D. McCalley, Major Professor
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Ames, Iowa

2001

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This is to certify that the Master's thesis of

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has met the thesis requirements of Iowa State University

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ABSTRACT

For many years, the electric power industry has been using optimization methods to help them solve the unit commitment problem, which is the problem of scheduling the production of electric power generating units, over a certain time horizon, in order to minimize the energy production costs. The referred time horizon is usually daily to weekly.

This work expands the traditional unit commitment problem to account for the effect of unit commitment schedules on security issues. Specifically, this thesis focuses on the identification of operational high-risk scenarios that can be mitigated by modifying unit commitment schedules. Furthermore, it also addresses a strategy for risk mitigation that consists on imposing adequate constraint into a longer-term unit commitment problem formulation (up to one year).

The proposed work involves using the concept of risk-based long-term sequential simulation to develop methods of strengthening security monitoring and decision-making capability for overload, low voltage, voltage instability, and cascading overload problems. The achievement of a good balance between security level and costs is the ultimate objective of the complete procedure.

CHAPTER 1. INTRODUCTION

1.1 BACKGROUND

The unit commitment problem (scheduling generator start-ups and shut-downs over a period of time to minimize the cost of serving expected loads) has been applied by the power industry and studied by researchers for decades. This is a complex mathematical optimization problem having both integer and continuous variables. Unit commitment solutions have traditionally been obtained for relatively short-term time frames (daily to weekly). This is because, in solving the unit commitment problem of a realistic size system and for a long time period, one of the main causes of difficulty is the involvement of a large number of variables, causing significant computational challenges. As a result, research efforts have concentrated on efficient, sub-optimal unit commitment algorithms that can be applied to realistic power systems and have reasonable storage and computation time requirements. The other reason to use short-term time frames is that the uncertainty of operating conditions, particularly load forecast, becomes great when unit commitment is solved for a longer time period ahead.

Secure operation is an enduring concern to electric utilities. The available techniques that deal with this issue can be generally grouped into two broad categories: deterministic and probabilistic approaches. Deterministic methods do not specifically recognize the probability of component failure, i.e. generating units, transmission lines, etc., in their formulation. But a probabilistic approach can be used to recognize the stochastic nature of system components and to incorporate these phenomena in a consistent evaluation of the reliability of an electric power system. Usually, unit commitment solutions do not account for risk as an overall index that reflects the security level of the system. In general, the unit commitment solutions that someway take into account the security problems into their formulation, only consider portions of the problem, e.g. introducing reserve constraints [1]. Though, unit commitment schedules can have significant effect on security levels due to several problems. Some methods that do incorporate security constraints directly into the unit commitment formulation have already been developed. These include formulations that integrate the security constrained optimal power flow or the risk constrained optimal power flow within the unit commitment. However, these approaches model security with constraints that impose a rigid limit to a certain security measurement. In addition, for long-term scheduling, these approaches are not viable due to their very computationally intensive characteristic.

It can be seen from the above that tools to support integrated electrical generation scheduling process and risk evaluation for a long-term horizon are far from satisfactory in the view of the inherent complexity and the sizes of practical problems. Therefore, an efficient approach to address this challenge is critically needed.

This thesis presents a way to study the relationship between unit commitment schedules and risk associated with security problems that will allow us to identify specific attributes of a unit commitment schedule that have significant influence on risk. A probabilistic approach is used to perform the risk assessment. The objective is to enable operational decision-maker to modify schedules to achieve the most secure system with minimum deviation from the economic optimum. As mentioned before, unit commitment solutions are typically computed on a daily or weekly basis. Today, however, operators need as much advanced information as possible, so motivation is there to look out further ahead, if possible. Since our objective is to look for high-risk scenarios, many possible future circumstances can be investigated to discover such scenarios.

1.2 PURPOSE OF THE WORK

The main goal of this research is to use risk-based assessment and long-term sequential simulation in developing a procedure to identify the relation between the unit commitment solution and risk variation.

Iowa State University has developed a simulator that performs a sequential long-term simulation of a power system on an hour-by-hour basis. This simulator implements a sequential trajectory of 8760 operating conditions for the time frame of interest (typically one year). Descriptions of its features will be addressed in Chapter 4 and more details can be found in [2]-[8]. The simulator will be used in order to evaluate the risk level incurred by the system at each hour, during one year.

Given an expected unit maintenance and unit commitment strategy for a future time period, a method is developed to use the sequential long-term simulator for studying the relation between the unit commitment and risk variation. The issues to be addressed in this work are:

- *Identification of undesirable unit commitment effects on risk*: Any unit commitment program can identify the specific times associated with an up or down transition for a unit. The unit commitment algorithm used in this research work also allows this. A procedure to identify undesirable unit commitment effects on risk is to inspect the risk variations and identify when they are caused by unit commitment transitions. Transitions that cause significant risk variation (especially shut-down transitions that cause significant risk increase) are good candidates to investigate regarding changing the unit commitment schedule. This procedure has been implemented, assessed for effectiveness, and specifications for refining and enhancing have been developed.

- *Identifying the most effective changes in unit commitment:* A heuristic method has been developed where the unit commitment program is rerun with the identified units constrained "on" during the identified high-risk time periods. Only one constraint is added for each unit commitment run, and the increase in yearly production costs due to the additional constraint is identified. The simulator is then rerun using the new unit commitment schedule to identify the decrease in cumulative risk associated with the constraint. This provides a change in cost and a change in risk for each additional constraint. Decision criteria for accepting the constraint are based on the change in cost and change in risk for each additional constraint.

1.3 THESIS ORGANIZATION

This thesis is divided into seven chapters. Chapter 1 includes the description of the research objectives and this overview. In chapter 2, several approaches used to solve the unit commitment problem are reviewed, and the solution method adopted is presented. The risk-based assessment concepts are described in chapter 3. Chapter 4 addresses some important features of the long-term sequential simulator. Chapter 5 refers to the procedure implemented to accomplish the objectives of the work (implement unit commitment adjustments based on risk assessment). The new electric industry structure, under a deregulated environment, is described in chapter 6, and this chapter also addresses the way unit commitment is performed within the market framework and how our approach could be implemented in this environment. To highlight the methodology described in the previous chapters, chapter 7 provides some simulation results obtained when using the IEEE Reliability Test System'96. Finally, chapter 8 summarizes the work and suggests possible future research directions.

CHAPTER 2. UNIT COMMITMENT

2.1 INTRODUCTION

For many years, the electric power industry has been using optimization methods to help solve the unit commitment problem, which is the problem of scheduling the production of electric power generating units, over a certain time horizon, in order to accomplish the best achievement in economy [9]. The referred time horizon for unit commitment-related decisions is usually daily to weekly, and our approach may certainly be used to investigate unit commitment within this time frame. However, it is also desired to develop a tool for investigating longer-term unit commitment schedules with the objective being to identify operational high-risk scenarios that can be mitigated by modifying unit commitment schedules. This tool can be used to probe possible future scenarios and identify various strategies for risk mitigation that can be communicated to the operator when the scenarios are encountered. In pursuing this line of thought, the work reported herein is applied to one-year unit commitment schedules, recognizing at the same time that approach is also very well suited to the daily to weekly schedules that are common in the industry today.

The problem solution must respect both generator constraints (such as output limits and minimum up or down times) and system constraints (such as hydro energy availability and loading requirements). The objective function should account for costs associated with energy production along with start-ups decisions. The resulting problem is a large-scale nonlinear mixed integer program.

The unit commitment problem has been under investigation since the early twenties [10], and consequently there are in existence many different mathematical ways to approach it [11], the result of the strong motivation for theoretical and practical works in this field. In theoretical sense, the problem is characterized as a non-linear, non-convex, mixed integer, optimization problem. Therefore, the solution effort of such a problem offers extensive possibilities for achieving interesting contributions to the field of optimization. On the other hand, the strong need for lower cost operating schedules on behalf of generating companies have motivated considerable activity for solving the unit commitment problem in practice.

Because of the unit commitment problem's size and complexity and because of the large economic benefits that could result from its improved solution, considerable attention has been devoted to algorithm development. Up to this time, an enormous amount of literature exists, and many approaches have been proposed to solve the unit commitment problem of hydro, thermal, and combined hydrothermal systems. In the next section, some of these methods are presented and their characteristics are discussed.

2.2 UNIT COMMITMENT SOLUTION METHODS

2.2.1 Priority List

The simplest unit commitment solution method consists of creating a priority list of units. After an exhaustive enumeration of all unit combinations at each load level, a simple shut-down or priority list scheme can be obtained in a heuristic ordering by operating cost combined with transition costs. The pre-determined order is then used to commit the units such that the system load is satisfied. More details about this approach can be found in [12].

One important weakness of this method is the enormous dimensionality that can be reached in this problem. Suppose there are four units in a system and any combination of them could serve the load. There would be a maximum of $2^4 - 1 = 15$ combinations to test. Therefore, the priority lists method of solution incurs an important weakness for large power systems with many generating units.

However, several modifications can be introduced in the priority list methods, in order to reduce the dimension of the problem. Even though the solution found is a suboptimal one, it will be a feasible solution obtained in a shorter time interval.

2.2.2 Dynamic Programming

Dynamic programming searches the solution space that consists of the unit's status for an optimal solution [13]. The search can proceed in a forward direction in time, from the initial hour to the final hour. Conversely, the algorithm can also be set up to run backward in time, starting from the final hour to be studied, back to the initial hour. The time periods of the study horizon are known as the stages of the dynamic programming problem. Typically each stage represents one hour of operation. The combinations of units within a time period are known as the states of the dynamic programming problem.

The forward approach has distinct advantages in solving the unit commitment problem. For example, if the start-up cost of a unit is a function of the time it has been off-line, then a forward dynamic program approach is more suitable since the previous history of the unit can be computed at each stage. Forward dynamic programming finds the most economic schedule by starting at the initial stage accumulating total costs, then backtracking from the combination of least accumulated cost starting at the last stage and ending at the initial stage. But if start-up ramps need to be pre-defined, the standard dynamic programming approach may encounter difficulty with these time dependent constraints. The start-up ramps model the output profile that each unit needs to follow in the first several hours after synchronization. They represent the thermal and mechanical restrictions imposed upon a plant when bringing a unit on line. Due to the fact that each combination of units will retain only one predecessor path, necessary links back to early stat options may be eliminated before it is obvious they are essential to the solution [14].

Dynamic programming builds and evaluates the complete decision tree to optimize the problem at hand. Therefore, as in the priority list approach, this method suffers from the dimensionality problem, because the number of states grows rapidly with the number of generating units to be committed. To reduce the search space and hence the dimension of the dynamic programming problem, several approaches have been adopted. However, this necessity of forcing the dynamic programming solution to search over a small number of commitment states to reduce the number of combinations that must be tested in each time period denotes a limitation to this method when applied to large power systems.

It should also be noted that additional constraints may not be added into the dynamic programming framework without major software changes.

2.2.3 Genetic Algorithms

The genetic algorithm emulates the optimization techniques found in nature (e.g. natural selection, survival of the fittest). In this technique, solution evaluation and randomized, structured exchanges of information between solutions are combined to obtain optimality. Genetic algorithms are considered to be robust methods because no restrictions on the solution space are made during the process [15]. The power of this algorithm comes from its ability to exploit historical information structures from previous solution guesses in an attempt to increase performance of future solution structures.

Genetic algorithms borrow the analogous biological terms for each step. They maintain a population of parameter set solution and iterate on the complete population. Each iteration is called a generation. The problem parameter set, including its environment, inputs, and outputs, is represented by a fixed length string of symbols, usually from the binary alphabet {0,1}. The string, called a chromosome, represents a single solution point in the problem space. The chromosome string consists of a genetic material in specific locations, called loci.

Each location contains a symbol or series of symbols, called genes, which assume values, called alleles [16], [17].

The initial population is usually created using a random number of generators, and then subsequent generations are formed from the initial population information. Therefore, it is important to provide a wide variety of genetic material to work from in the base population. Thus, the population size must be chosen large enough to supply sufficient genetic structures to allow unrestricted solution space search.

The evaluation of the chromosome string is accomplished by decoding the encoded symbols and calculating the objective function for the problem using the decoded parameter set. The result of the objective function calculation is used to calculate the value of the string with respect to all other chromosome strings within the population. Implementation of an objective function and constraints in a genetic algorithm are realized within the fitness function. The fitness function acts as a pseudo objective function, since it is a raw measure of the solution values. Inclusion of the constraints in the fitness function requires the introduction of tolerances in satisfying the constraint equations. The application of this method to the unit commitment problem uses the payoff information of an objective function to evaluate optimality.

If algorithm control or emphasis to certain problem objectives or constraints is desired, scaling factors are added. The selection of these scaling parameters in the fitness function evaluation equation is a crucial initial tuning process. Furthermore, scaling parameters selection may present a major obstacle in solving more complex problems for which there are no known solutions for comparison.

2.2.4 Branch-and-Bound

The branch-and-bound approach determines a lower bound to the optimal solution and then finds a near-optimal feasible commitment schedule [18]. The branch-and-bound tree is searched for the best solution. The lower bound can be determined from a dual optimization problem that uses the Lagrangian relaxation technique. This technique enables the problem to be solved satisfactorily from the mathematical viewpoint, but it becomes impracticable due to computational cost and memory size requirement when the system involves some tens of units [19].

2.2.5 Lagrangian Relaxation

The Lagrangian relaxation method has gained the most research interest among other proposed approaches mainly because of its internal ability to provide fast, unit-wise decentralized solution and its flexibility to incorporate the majority of constraints [20], [21]. This technique is based on a dual optimization approach. The dual problem is formulated by introducing Lagrange multipliers and by incorporating constraints into the objective function [22].

In this technique, the unit commitment problem is decomposed into a master problem and more manageable subproblems that are solved iteratively until a near-optimal solution is obtained. The subproblems are solved independently and each one determined the commitment of a single generating unit. The problems are linked by Lagrange multipliers that are added to the master problem to yield a dual problem.

The dual problem has lower dimension and is easier to solve. For the unit commitment problem, the primal function is always greater than or equal to the dual function. The difference between the two functions yields the duality gap for which the primal function is an upper bound. The duality gap provides a measure of the near optimality of the solution.

For large, real size, power system unit commitment calculations, the duality gap does become quite small as the dual optimization proceeds, and its size can be used as a stopping criterion. However, the algorithm can cycle resulting in unstable convergence at the end, meaning that some units are being switched in and out, and the algorithm never terminates. Furthermore, there is no guarantee that when the duality gap is small and satisfies the stopping criterion that the solution will be feasible. Also, the optimal solution may not be unique, as shown in [23]. This means that some problems can occur while using Lagrangian relaxation as an auction method for bidding in a deregulated environment, since identical or similar generation units can prevent the algorithm from finding an optimal solution, resulting in contested auctions.

The quality of the solution depends on the sensitivity of the commitment to Lagrange multipliers. Slow and unsteady convergence of Lagrangian relaxation techniques has always been a problem in finding the global optimum solution, which means that unnecessary commitment of generation units may occur, resulting in higher production costs. Many of the Lagrangian relaxation unit commitment programs use a few iterations of a dynamic programming algorithm to get a good starting point, then run the dual optimization iterations, and finally, at the end, they use heuristic logic or restricted dynamic programming to get to a final solution. The result is a solution that is not limited to search windows, such as are required in strict application of dynamic programming.

However, this technique may also have computational trouble with large problems, and for long time horizons it is almost impracticable as a result.

2.2.6 Constrained Unit Commitment Approaches

There are some approaches that intend to solve the unit commitment problem with a direct incorporation of security constraints into its formulation. The most rigorous way to do this is to incorporate within a unit commitment the security constrained optimal power flow (SC-OPF) [24] or the closely related risk-constrained optimal power flow (RC-OPF) [25], where security-related constraints are explicitly represented within the optimization routine.

For long-term unit commitment scheduling, these approaches would be very computationally intensive. In addition, the level of information quality available for long-term unit commitment scheduling, because it is influenced by forecasting error, may not justify this level of refinement in analysis. Thus, the long-term unit commitment scheduling need take only a high-level, global view of unit commitment adjustments, to identify future situations that are clearly high risk and require adjustments that bring about significant changes in risk level, leaving refined unit commitment adjustments to be made based on short-term assessment. Some related work includes [26], [27].

2.3 UNIT COMMITMENT APPROACH ADOPTED

2.3.1 Introduction

As mentioned before, unit commitment software is traditionally used as an operational tool to identify near-term unit commitment schedules. In this case, the operational goal is to set a specific unit commitment schedule, and therefore the assessment must accurately reflect the actual condition of the short-term time interval. As a result, unit commitment is normally computed on a day-ahead or week-ahead basis, because load forecast error for longer periods causes too much uncertainty in the computed solution. The approach developed in this research work applies to this more traditional use of unit commitment software; in addition, it is intended that it will enable study of longer-term unit commitment solutions as well so as to provide the engineer with the ability to probe possible future scenarios and identify various strategies for risk mitigation that can be communicated to the operator when the scenarios are encountered. Of course, unit commitment solutions for longer time periods are more computationally intense, and as a consequence, a very efficient, but approximate, unit commitment approach is used to determine a full year's solution [28]. This schedule would serve as long-term plan, which can be adjusted by more accurate short-term calculations.

Long-term unit commitment problems are inherently stochastic. The stochastic character results from uncertainties in:

- Customer load requirements;
- The natural inflows into hydro reservoirs;
- Times between forced outages, and also repair and maintenance times of power production units and transmission lines.

The complexity of long-term problems is further increased by conceptual and analytical difficulties in defining appropriate optimization criteria for a long-term period. Furthermore, most of the previously proposed techniques are short-term oriented algorithms. All of this makes long-term dispatching quite challenging.

When defining the approach presented in this thesis to solve the unit commitment, one should respect two important design requirements:

- It must be computationally feasible;
- It must be able to easily handle the incorporation of new constraints.

The first requirement is related to the long-term characteristic itself, i.e., the inherent dimension of the problem. The second characteristic reflects the objective of proposing some adjustments to the unit commitment solution in order to mitigate the risk incurred by the system. To do that, new constraints will systematically be introduced into the unit commitment problem formulation.

2.3.2 Problem Formulation

Given an operation planning horizon of T hours and a system with N available units and load demand forecast P_D^t, $t = 1 \ldots T$, the problem is to determine the commitment status of each unit, as well as unit outputs, so as to minimize total operating cost. It can be mathematically formulated as follows:

Objective function:

$$\text{Min} \qquad \sum_{i=1}^{n_t}\sum_{t=1}^{T}\left(F\left(P_{ti}^t, U_i^t\right) + S_i^t\right) \tag{2.1}$$

Subject to:

$$\sum_{i=1}^{n_t} P_{ti}^t + \sum_{i=1}^{n_n} P_{ni}^t + \sum_{i=1}^{n_h} P_{hi}^t = P_D^t\left(1 + P_{loss}^t\right) \qquad t = 1 \ldots T \tag{2.2}$$

$$\sum_{t=1}^{0.25T}\sum_{i=1}^{n_h} P_{hi}^t = E_1 \tag{2.3}$$

$$\sum_{t=0.25T+1}^{0.5T}\sum_{i=1}^{n_h} P_{hi}^t = E_2 \tag{2.4}$$

$$\sum_{t=0.5T+1}^{0.75T}\sum_{i=1}^{n_h} P_{hi}^t = E_3 \tag{2.5}$$

$$\sum_{t=0.75T+1}^{T}\sum_{i=1}^{n_h} P_{hi}^t = E_4 \tag{2.6}$$

$$U_i^t P_i^{\min} \le P_i^t \le U_i^t P_i^{\max} \qquad i = 1 \ldots N,\ t = 1 \ldots T \tag{2.7}$$

and the minimum up and down time constraints.

The objective function of the long-term unit commitment problem, which is to be minimized, is the total fuel cost of thermal units. The first constraint, equation (2.2), reveals the power balance. Equations (2.3)-(2.6) account for the hydro energy constraints and finally equation (2.7) refers to the units limits. The minimum up and down time constraints are imposed upon only thermal units to prevent the thermal stress and high maintenance costs due to excessive unit cycling. These constraints are that once a unit is started up (shutdown), it cannot be shutdown (started up) for a given number of hours.

The notation is as follows:

T : number of hours for one year;

N : number of available generating units in the system;

n_t : number of thermal units, at time t, that are not in maintenance;

n_n : number of nuclear units, at time t, that are not in maintenance;

n_h : number of hydro units, at time t, that are not in maintenance;

P_{ti}^t : generation in MW of thermal unit i at hour t;

P_{ni}^t : generation in MW of nuclear unit i at hour t;

P_{hi}^t : generation in MW of hydro unit i at hour t;

P_D^t : total load in MW at hour t;

P_{loss}^t : power loss factor (dimensionless) at hour t;

U_i^t : unit state (1 for up and 0 for down) of thermal unit i at hour t;

S_i^t : start-up cost in dollars for unit i at hour t;

$F(.,.)$: operational cost in dollars for thermal unit i (it is a function of P_{ti}^t and U_i^t);

E_1 : total available hydro energy in MW-hrs for spring season;

E_2 : total available hydro energy in MW-hrs for summer season;

E_3 : total available hydro energy in MW-hrs for fall season;

E_4 : total available hydro energy in MW-hrs for winter season.

2.3.3 Our Approach

For realistic size systems and for the time period considered, to obtain a computationally feasible solution approach, the priority list method is very attractive, since it is simple, fast, and gives a feasible, even though suboptimal, solution. Furthermore, it is flexible with regard to incorporating new constraints.

As a consequence, the unit commitment method adopted is a heuristic approach based on Lagrangian relaxation techniques and also on priority list schemes [29]. The nuclear units are dispatched at full capacity, when they are not in maintenance. In other words, it is imposed a "must run at the maximum" constraint to these units. This assumption is reasonable since typically, nuclear units present the minimum average production cost among all the thermal units. The hydro units are dispatched to meet the seasonal hydro energy constraints (equations 2.3-2.6), and the cost for using hydropower is assumed to be zero. Finally, the thermal units are scheduled according to their incremental heat (cost) rate curves by solving an economic dispatch sub-problem using the lambda-iteration method.

The incremental heat curve is a very important characteristic of a thermal unit. It represents the evolution of the incremental heat rate ($\Delta H/\Delta P$ expressed in Btu/MWh) with the net power output of the unit (P expressed in MW), as it is shown in Figure 2.1. This characteristic is widely used in economic dispatching of the unit, and it can easily be converted to an incremental fuel cost characteristic by multiplying the incremental heat rate in Btu/MWh by the equivalent fuel cost in terms of \$/Btu. Frequently this curve is approximated by a sequence of straight-line segments, as it will be done in this research work.

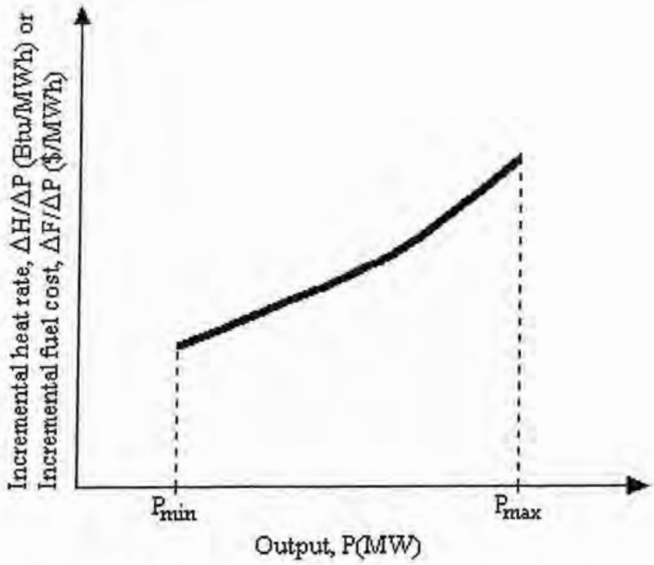


Figure 2.1 – Incremental heat (cost) rate characteristic

As usual, λ is defined as the Lagrange multiplier on the power balance equation for the economic dispatch sub-problem. The KKT conditions require that (1) the minimum cost operating condition for the thermal units occur when the incremental cost rates of all regulating units are equal to the value λ and (2) the sum of the power outputs must be equal to the power demanded by the load and that was not supplied by the other generating units (nuclear and hydro). In addition, there are two inequalities that must be satisfied for each of the units. That is, the power output of each unit must be greater than or equal to the minimum power permitted and must be less than or equal to the maximum power permitted on that particular unit.

The lambda iteration method is a very fast optimization algorithm for the economic dispatch problem, since it converges very rapidly. The idea is to start setting a value for λ and computing the corresponding outputs for the thermal units, according to their incremental fuel cost characteristics. Certainly, the first guess for λ will be incorrect. If the value of incremental cost is such that the total power output is too low, then the λ value must be increased and another solution tried. With two solutions, one can interpolate (or extrapolate) the two solutions to get closer to the desired value of the total power (for this it is adopted a bisection algorithm). When the difference between the sum of the outputs and the load these machines need to satisfy is less than a defined tolerance, then the solution is found. Otherwise, if that difference is greater than the tolerance, the process should continue adjusting the value λ.

The Lagrange function of the complete mathematical problem presented in the previous section can be expressed as follows:

$$L\left(P_{ti}^t, U_i^t, \lambda^t, \gamma^s\right) = \sum_{i=1}^{n_t}\sum_{t=1}^{T}\left(F\left(P_{ti}^t, U_i^t\right) + S_i^t\right) + \\ + \sum_{i=1}^{T}\lambda^t\left(P_D^t\left(1 + P_{loss}^t\right) - \sum_{i=1}^{n_t} P_{ti}^t - \sum_{i=1}^{n_n} P_{ni}^t - \sum_{i=1}^{n_h} P_{hi}^t\right) + \sum_{s=1}^{4}\gamma^s\left(E_s - \sum_{t=0.25T(s-1)+1}^{0.25sT} P_{hi}^t\right) \tag{2.8}$$

The steps of the complete procedure are:

1. Calculate the incremental fuel cost curves for all thermal units. $P_{ti}^t(\lambda)$ is the output for the thermal unit i corresponding to incremental value λ, at time t. Among all curves, the minimum λ is defined to be λ_{min} and the maximum is λ_{max}. Let $s = 1$, $t = 1$.

2. Set $\lambda_1 = \lambda_{\min}, \lambda_2 = \lambda_{\max}$, $P_{ni}^t =$ capacity of the nuclear units available, and $C_h^t = 0$, where C_h^t is the hydropower needed at hour t.

3. If $\sum_{i=1}^{n_t} P_{ti}^t(\lambda_{\max}) + \sum_{i=1}^{n_n} P_{ni}^t < P_D^t(1 + P_{loss}^t)$, the total hydro unit output needed is

   $C_h^t = P_D^t(1 + P_{loss}^t) - \sum_{i=1}^{n_t} P_{ti}^t(\lambda_2) + \sum_{i=1}^{n_n} P_{ni}^t$, go to step 5. If not, continue to step 4.

4. Use bisection to find λ_{opt}^t, such that $\sum_{i=1}^{n_t} P_{ti}^t(\lambda_{opt}^t) + \sum_{i=1}^{n_n} P_{ni}^t < P_D^t(1 + P_{loss}^t) - C_h^t$.

5. If $t < T$, set $t = t + 1$, go to step 2.

6. If $\sum_{t=0.25(s-1)T+1}^{0.25sT} C_h^t < E_s$, this means the seasonal hydro energy has not been used up, use bisection to find a threshold for $\sum_{i=1}^{n_t} P_{ti}^t$, allocate the exceeding thermal output to the hydro units until $\sum_{t=0.25(s-1)N+1}^{0.25sN} C_h^t = E_s$. Let $s = 2$, go to step 2.

   If $\sum_{t=0.25(s-1)T+1}^{0.25sT} C_h^t = E_s$, let $s = 2$, go to step 2.

   If $\sum_{t=0.25(s-1)T+1}^{0.25sT} C_h^t > E_s$, this means thermal, hydro and nuclear generation cannot meet the load in season load, the maintenance schedule has to be revised. Reschedule maintenance and start from step 1.

7. Dispatch the hydro units according to C_h^t. Dispatch the thermal units according to $\sum_{i=1}^{n_t} P_{ti}^t(\lambda_{opt}^t) = P_D^t(1 + P_{loss}^t) - C_h^t - \sum_{i=1}^{n_n} P_{ni}^t$.

8. Adjust the thermal units to meet the minimum up and minimum down constraints.

The solution obtained with this procedure is a suboptimal one, however, it always provides good solutions for the purposes of long-term unit commitment. Moreover, the power flow calculations converge for all hours.

CHAPTER 3. RISK ASSESSMENT

3.1 INTRODUCTION

Risk-based security assessment computes a quantitative risk index to reflect the system's exposure to failure [30] - [31]. The system risk associated with a forecasted loading condition $X_{t,f}$ is given as a function of the various contingencies E_i, according to:

$$Risk\left(Sev \mid X_{t,f}\right)=\sum_{i}\sum_{j}\Pr(E_i)\Pr\left(X_{t,j} \mid X_{t,f}\right)Sev\left(E_i, X_{t,j}\right) \tag{3.1}$$

where $\Pr(E_i)$ is the outage probability of contingency E_i, $X_{t,j}$ is the j[th] possible loading condition, $\Pr(X_{t,j}|X_{t,f})$ provides the probability of this condition and is obtained from a probability distribution for the possible loading conditions, and finally $Sev(E_i,X_{t,j})$ is the system severity of contingency E_i under the j[th] possible operating condition X_t. Severity is an unavoidable consequence of a specified condition. It provides a quantitative evaluation of what would happen to the power system in the specified condition.

Transmission line or transformer overload, bus low voltage, voltage instability, and cascading overload are possible impacts that can result from a given contingency E_i and operating condition X_t, each resulting in a different kind of risk, called the overload risk, low voltage risk, voltage instability risk, and cascading overload risk, respectively. The system composite risk can be calculated as the sum of these four kinds of risk, as follows:

$$\begin{aligned} CompositeRisk(Sev \mid E_i, X_t) = {} & OverloadRisk(Sev \mid E_i, X_t) + LowVoltRisk(Sev \mid E_i, X_t) + \\ & + VolInstRisk(Sev \mid E_i, X_t) + CascadingRisk(Sev \mid E_i, X_t) \end{aligned} \tag{3.2}$$

This means that different types of risk associated with different types of security problems can be added up together and used as a comprehensive indicator for system security. In [29], a useful tool has been developed to perform the maintenance scheduling for generating units and transmission facilities using this idea of risk-based security assessment. In this research project this risk index is used to adjust or refine the unit commitment schedule.

3.2 SEVERITY FUNCTIONS

3.2.1 Introduction

Risk-based security assessment requires modeling of severity functions [32]. The severity functions are used to quantify inevitable consequences or impact associated with the security problems, including load interruption, equipment damage, and opportunity costs due to equipment outage. The development of the severity function is typically difficult in most probabilistic risk assessment problems, including power systems risk-based security assessment.

In this research work, the security problems considered are overload of circuits (including transmission lines and transformers), low voltage of buses, voltage instability, and cascading overload. The individual severity functions of low voltage and overload quantify the severity, impact, consequence, or cost of the corresponding bus or circuit. They capture the severity of each component in the system, so they are denoted as component's severity functions. The severity functions for voltage instability and cascading overload capture severity, impact, consequence, or cost of the whole system. As they reflect the severity of the whole system, and cannot be decomposed by component or area, they are referred to system's severity functions.

In order to develop the model for the severity functions, the following criteria was established:

- They should accurately reflect severity between the various events that can occur, to enable the calculation of a composite index;
- They should be physically meaningful;
- They should be simple, easy to understand and use, and should not require large data collection effort and computation;
- They should increase continuously as the performance index (e.g., flow, voltage, loading margin, cascaded lines) gets worse. This means they should be able to measure the extent of the violation.

There are various ways to characterize the severity function. One approach is to assign an economic value to each possible outcome assessed as an impact. Then the corresponding risk has explicit economic meaning in that it represents the expected cost due to possible insecurity problems. It measures the economic consequence of an uncertainty weighted by its probability of occurrence. This significant property provides a direct bridge between power system economics and reliability, in that it is a mean to explicitly include reliability in ordinary economic decision-making problems.

However, economic valuation of severity has some drawbacks for operational use. First, it does not capture the physical attributes of the network and therefore may not be useful to engineers and operators in providing intuition and insight regarding the engineering problems they face. In addition, economic valuation of security problems contains great uncertainty that is not present in physical quantification of security problems. Although this uncertainty can be quantified using higher moments, such as variance, it is possible that the expected value (i.e., the risk) would provide a false sense of precision and consequently be used inappropriately.

For these reasons, severity functions that are closely related to the physical attributes of the network, particularly the component ratings, were elected to be used in this research project. Network-based (non-economic) risk indices may still be used in economic decision-making. For example, a common multi-criteria decision-making formulation minimizes a function like $\alpha_1 f_1+\alpha_2 f_2+\alpha_3 f_3$ where the f's are individual objective functions and the α's are the weights on these functions. Economic objectives can be combined with network-based risk functions in such a formulation by appropriate choice of the α's.

The traditional deterministic approach for quantifying the impact of a security problem uses the ratings of components, for example, the load flow rating of a transmission line or transformer, the voltage limit at a bus, etc. This is attractive in operations where engineers prefer indices that reflect physical attributes of the network that are easily understandable. If the severity functions are defined based on this deterministic approach, they can be very simple, physically meaningful, and easy to understand. These severity functions are called rating-based severity functions.

The next four sections present the rating-based severity functions used for overload, low voltage, voltage instability, and cascading overload risk calculations, respectively.

3.2.2 Severity Function for Overload Risk

The severity function for overload risk calculations is defined specifically for each circuit (transmission lines and transformers). The load flow in each circuit determines the overload severity of that circuit. Based on the circuit's rating, the severity function for overload is illustrated in Figure 3.1.

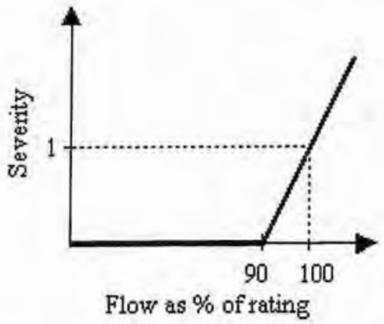


Figure 3.1 – Rating-based severity function for overload risk calculation

For each circuit, its severity evaluates to 1.0 at the deterministic limit (100 % of rating) and increases linearly as the load flow exceeds the limit, in such a way that it is zero when the flow is 90 % of rating. For load flows below this value the severity is assumed to be zero.

3.2.3 Severity Function for Low Voltage Risk

The severity function for low voltage is defined in particular for each bus. The voltage magnitude in each bus determines the low voltage severity of that bus. The severity function for low voltage risk calculations is presented in Figure 3.2.

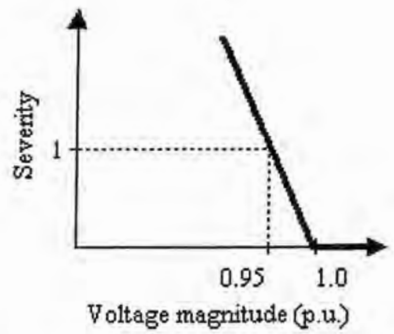


Figure 3.2 – Rating-based severity function for low voltage risk calculations

For each bus, its severity evaluates to 1.0 at the deterministic limit (0.95 p.u.) and increases linearly as voltage magnitude drops below the limit. When the voltage magnitude equals 1.0 p.u. the severity evaluates to zero and it is like that for voltages above 1.0.

3.2.4 Severity Function for Voltage Instability Risk

The severity function for voltage instability is a system severity function rather than a component severity function. For a particular operation point, the amount of additional load that cause a voltage collapse is called the loading margin. Hence, loading margin can be used as the indicator of the system's safety level with respect to voltage instability. The larger the loading margin the safer the system. In fact, both loading margin and loadability, shown in the P-V curve illustrated in Figure 3.3, can be used to measure the security level with respect to voltage instability, because the difference between the two is the actual system load.

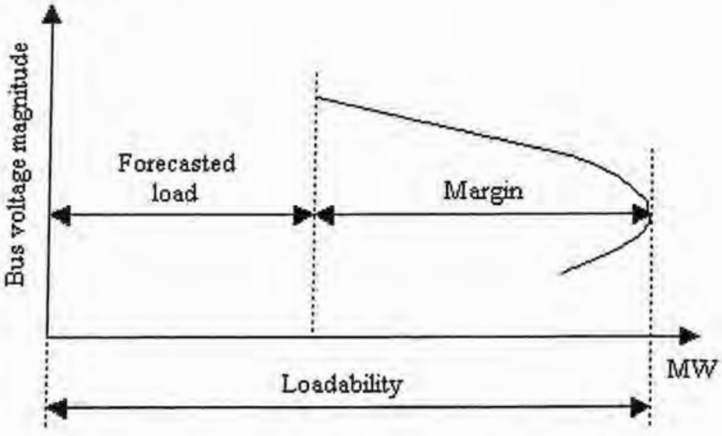


Figure 3.3 – Concept of loadability and margin

The loadability is an index reflecting the distance between the present system condition and the voltage collapse point (the bifurcation point). To get this loadability value, the system can be stressed by increasing its load or decreasing its generation continuously along pre-defined directions, according to how the load and generation is expected to change, until it reaches the bifurcation point. Then the loadability equals the present load plus the increased load or decreased generation. There are several effective ways to find the loadability value of a system [33], [34]. In this thesis, the continuation power flow method is used to detect proximity to voltage collapse [35]. Let us define "%margin" as the percentage difference between the forecasted load and loadability:

$$\%margin = \frac{Loadability - Forecasted\_Load}{Forecasted\_Load} * 100\% \tag{3.3}$$

For the voltage instability problem, the concept of "%margin" is used to define the severity function that is illustrated in Figure 3.4.

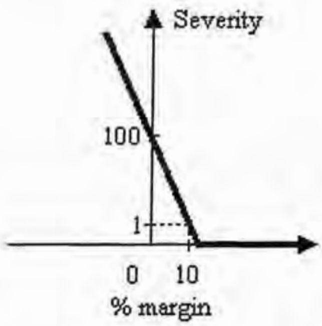


Figure 3.4 – Rating-based severity function for voltage instability risk calculations

The severity evaluates to 1.0 when "%margin" is 10 %, where this percentage is chosen as the minimum safe margin. If "%margin" is negative, voltage instability will occur in the given contingency state for the particular operating condition. The actual effects of such an outcome are not possible to identify with just a power flow program, as the system dynamics play a heavy role. Nonetheless, it is assured to say that the consequence is very severe, and generally unacceptable under any conditions. It should therefore be assigned to it a number K much larger than 1.0. The value of 100 was chosen to represent the severity when "%margin" equals zero and varies linearly with "%margin" otherwise.

3.2.5 Severity Function for Cascading Overload Risk

The severity function for cascading overload risk is a system severity function, like the severity function for voltage instability risk, and is illustrated in Figure 3.5.

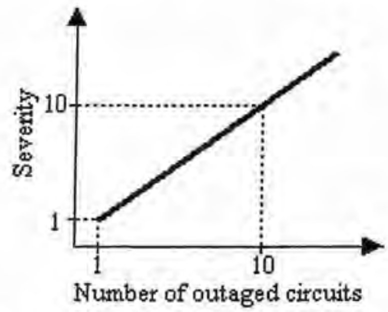


Figure 3.5 – Rating-based severity function for cascading overload risk calculations

The cascading severity function indicates that the severity is the number of cascaded circuits. A fast DC load flow algorithm is used to repetitively remove overloads circuits until either a case is reached where there are no overloads, or a specific number of overloads is identified, beyond which the system is considered to have suffered a collapse. In this case, the cascading overload severity is assigned to be K, which indicates the severity of a collapse from cascading overload is equivalent to the severity of a collapse from voltage instability.

3.3 MODELING OF UNCERTAINTIES

3.3.1 Introduction

In section 3.1, it was pointed out that severity function and uncertainty are two important issues for risk calculation. Equation (3.1) reveals that there are two kinds of uncertainties that are considered: one is related to the operating conditions $\Pr(X_{t,j}|X_{t,f})$ and the other is associated with the contingencies $\Pr(E_i)$. The following two sections describe the mathematic models used to characterize them.

3.3.2 Uncertainty of Contingency

Different components have different yearly failure rates. For example, the yearly failure rate of a transformer is typically less than that of a transmission line. For transmission lines, the yearly failure rate of a 500 kV line is less than that of a 69 kV line. The difference in the failure rates of components means that the failure probabilities of components are different. Therefore, the probabilities of contingencies are also different. The events E_i are assumed to be Poisson distributed. So, the probability mass function is given by [36]:

$$\Pr(E_i) = \left(1 - e^{-\lambda_i}\right) * e^{-\sum_{j \neq i} \lambda_j} \tag{3.4}$$

where λ_i is the occurrence rate of contingency i.

3.3.3 Uncertainty of Operating Condition

The aim of security assessment is to evaluate the security level at a future time t given that the forecasted operating condition at that time period t is $X_{t,f}$. The operating condition of the future time t is uncertain, but it is appropriate to model the probability distribution of X_t given $X_{t,f}$ with a normal distribution having a mean equal to the forecast. Under this assumption, the voltages and branch flows of X_t follow the Multi-Variate-Normal (MVN) distribution [37] and the loadability of voltage instability follows the Normal distribution. The objective is to obtain the probability distributions of voltage Pr(V| E_i, X_t), branch flow Pr(P| E_i, X_t), and load margin Pr(L_m | E_i, X_t), where E_i is a contingency state.

The uncertainty in operating conditions is captured by identifying specific operating parameters that cause this uncertainty. These include load distribution factors among load buses, load power factors, and generation participation factors. These parameters are random in the future, and is assumed that they follow a MVN distribution around their expected values, and their deviations, although random, are small enough such that linear approximation of these measures (voltage, branch flow, and loadability) with respect to these random parameters is valid.

Let $E(\underline{K}_p)$ be the expectation of these parameters, where the parametric column vector $\underline{K}_p$ includes all the uncertain operating parameters. Based on the given expectation of $\underline{K}_p$, i.e., a given uncertain operating parametric pattern, a continuation power flow or other techniques ([33], [34], and [35]) provides an expectation of loadability and the loadability sensitivities $\underline{S}_p$ with respect to these parameters. The load flow provides the expectation of voltage and branch flow, and the voltage and branch flow sensitivities $\underline{S}_p$ with respect to these parameters. Then, according to the assumption that the parameters' deviations are small enough to permit linear approximation of these measures (voltage, branch flow, and loadability) with respect to the random parameters, it follows that:

$$Y_t = E(Y_t) + \underline{S}_p^t \times \left(\underline{K}_p - E(\underline{K}_p)\right) \tag{3.5}$$

where Y_t are the specific performance measures (loadability, bus voltage, and branch flow). They are now random due to the random parameters $\underline{K}_p$.

By the normality assumption of the parametric deviations, $\underline{K}_p$ follows a MVN distribution with mean vector $E(\underline{K}_p)$ and variance-covariance matrix V_p.

$$\underline{K}_p \sim MVN\left(E(\underline{K}_p),\ \mathbf{V}_p\right) \tag{3.6}$$

where $E(\underline{K}_p)$ is the vector of expected system parametric scenario, and V_p is the variance-covariance matrix of these parameters. The elements of the variance-covariance matrix represent both the variances of each parameter and the correlation with respect to deviation of other parameters. This matrix can be estimated from the sample statistics of historical data.

It can be proven that Y_t, a linear function of the MVN distributed $\underline{K}_p$ also follows a Normal distribution. Its expected value is $E(Y_t)$, and the variance is $\underline{S}'_p \times \mathbf{V}_p \times \underline{S}_p$. The probability distribution of these measures is therefore,

$$Y_t \sim N\left(E(Y_t),\ \ \underline{S}'_p \times \mathbf{V}_p \times \underline{S}_p\right) \qquad (3.7)$$

and it depends on the value of the parameters, their variability, and how they correlate with each other.

3.4 CONTINGENCY SET

For cumulative risk assessment, selection of a suitable contingency set is quite important. The criterion utilized here is that any contingency having outage probability exceeding a certain threshold should be included.

For the test system IEEE RTS-96 that will be addressed in chapter 6, both branch outages and unit outages are considered. For unit outages, only single unit outage is taken into account. For branch outages, both single branch outage and common mode outage are included.

3.5 BENEFITS OF RISK INDEX

It is useful at this point to summarize the benefits of risk index not available with the traditional security assessment methods:

- *Quantitative index*: It provides a quantitative index that reflects security level in a condensed fashion. This not only allows efficient comprehensibility by the operator but also facilitates inclusion in formal decision-making paradigms.

- *Looking ahead*: A major weakness in traditional security assessment practices is that the assessment is performed with the latest state estimation, which represents a past condition, but the decision based on this assessment is for a future condition. Risk index provides assessment for a forecasted future, accounting for uncertainties, and therefore provides that the assessment is made on conditions corresponding to the time for which the decision will become effective.

- *Accounting for uncertainty*: Because risk index is used to assess near-future conditions rather than past conditions, it is necessary to introduce the ability to model uncertainties. (Here, "near-future" means one to several hours ahead.) The most influential uncertainties, relative to overload, low voltage, voltage instability, and cascading overload performance, include contingencies that affect network configuration (topology and unit commitment) and load level. The effects of these uncertainties are included in the probabilistic risk indices, as presented in section 3.3.

- *Accounting for severity*: The set of severity functions used to compute the risk indices were developed in section 3.2. They provide that the results reflect a probabilistic expectation of deterministic violations during the next time interval.

- *Decomposability of indices*: A unique feature of the risk indices is that they are highly decomposable. As a result of this feature, risk views may be obtained in terms of any user-selected combination of network level (system, regional, or component), contingency (all, N most risky, or user-specified), and problem type (overloads, low voltages, voltage instability, or cascading overload). This provides that the user can observe high-level system or regional views of risk, or, starting from these high-level views, the user may efficiently narrow the assessment on specific high-risk problems.

CHAPTER 4. LONG-TERM SEQUENTIAL SIMULATOR

4.1 FRAMEWORK

As mentioned in section 1.2, the long-term sequential simulator implements a sequential trajectory of operating conditions for the time frame of interest, performing a sequential long-term simulation of a power system on an hour-by-hour basis. The system trajectory model is critical for risk assessment. If it is chosen too simple, accuracy cannot be guaranteed. On the other hand, if the model is very complex, computation is too burdensome. In [28] two classes of system trajectory models are discussed, namely, the snapshot models and the sequential trajectory models.

In the snapshot models several typical snapshots of loading are chosen according to experience. For each snapshot, the unit commitment is arranged and reliability indices are computed [38], [39]. Because of the simplicity of these models, risk assessment can be performed fairly quickly. However, there is no guarantee to capture peak risk time periods, because they may not occur at the loading conditions chosen to define the snapshots.

Sequential trajectory models simulate the system trajectory hour-by-hour, over the whole year. Therefore, it has to calculate maintenance schedule and unit commitment for generators. Then the risk assessment is calculated based on the simulated trajectory or trajectories. One such model is called the sequential Monte Carlo simulation model [40]. The main disadvantage of this technique is that to achieve statistical convergence, a large number of sequential trajectories are required, making the computational burden unwieldy.

The trajectory model used in the long-term sequential simulator belongs to the second class presented above. But in contrast to the Monte Carlo simulation model, which studies multiple loading trajectories, only a single expected trajectory and associated variance is used. This is formed by developing an hour-by-hour load forecast, identifying and modeling the load forecast error, identifying a contingency set, identifying a maintenance schedule for all generation units, and developing a unit commitment plan and corresponding dispatch. This approach is called the sequential mean-variance (SMV) simulation. In summary, the SMV model is more accurate than the snapshot models, is faster than the sequential Monte Carlo model, is risk decomposable, and can capture peak risk time periods accurately. The complete framework of the long-term SMV simulator is presented in Figure 4.1.

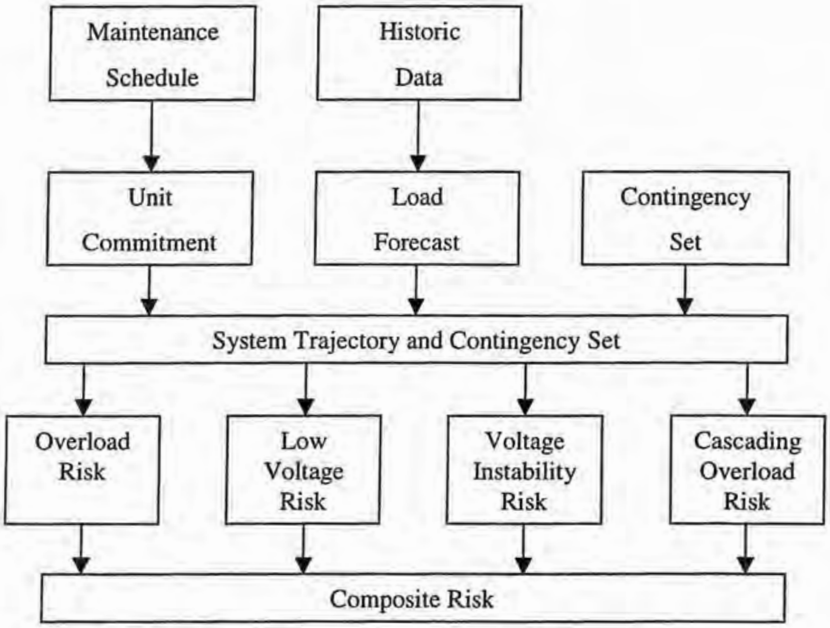


Figure 4.1 – Framework of the long-term sequential simulator

4.2 IMPORTANT FEATURES

As explained before, the approach used in the long-term sequential mean-variance simulator evaluates a trajectory of hourly operating conditions over a given period of time, such as one year. Its key features are:

- *Hourly assessment*: In making a one-year risk computation, the assessment is not based on a limited number of worst case loading conditions. In fact, some components may see their highest risk during off-peak or partial-peak conditions, when weak network topologies, weak unit commitment patterns, or unforeseen flow patterns are more likely to occur.

- *Sequential simulation*: Load-cycles, weather conditions, or maintenance strategies are examples of chronological dependent constraints that can affect security levels in ways that the snapshot models cannot capture. However, simulations that are sequential in time have the ability to take into account these inter-temporal dependencies.

- *Use of risk*: The risk index used in this research work provides an appropriate measure of security level by reflecting likelihood and severity of various events. Identifying the risk variation over time provides an indication of when, how long, and how frequently a high-risk period occurs.

4.3 SPEED ENHANCEMENTS

The objective of our use of sequential simulation is to perform risk assessment for each hour in the year. If there are N contingencies, 8760 x N different risk assessments must be performed. This is computation-intensive, so decreasing the computation time is an important concern. The following two sections describe a number of approaches used to achieve this goal (speed enhancement).

4.3.1 Decrease the Frequency of Calculation in the Simulator

In the standard SMV simulation method, the computations are performed every hour. However, this number of calculations can be reduced without diminishing the integrity of the resulting information content. The idea is to use a simple comparison between the next hour's conditions and previously encountered conditions. If this comparison indicates that two conditions are *sufficiently similar*, then the computations for the next hour can be avoided and the risk value is assumed to be the same. The same reasoning can be used in finding similar days or even similar weeks. To identify the similar hours the following method is used:

1. Determine the previous hours that have the same topology as that of next hour. Then compare the load profile and generation profile of next hour, denoted as hour j, with that of those hours. If for previous hour i, for all buses k, the following criteria are satisfied, hour i is said to be similar to the next hour. In this case, the result of hour i is used as the result of the next hour.

$$abs\left(\frac{P_{gki} - P_{gkj}}{P_{gki}}\right) < 0.01 \text{ and } abs\left(\frac{P_{gki} - P_{gkj}}{P_{gkj}}\right) < 0.01$$

$$abs\left(\frac{P_{lki} - P_{lkj}}{P_{lki}}\right) < 0.01 \text{ and } abs\left(\frac{P_{lki} - P_{lkj}}{P_{lkj}}\right) < 0.01$$

Here P_{gki} is the generation at bus k at hour i and P_{lki} is the load at bus k at hour i.

2. If there is no previous hour that has the same topology as that of next hour, or if none of the hours with the same topology satisfy the criteria presented above, then proceed as follows:
    a) Calculate the load flow of the next hour;
    b) Identify the branch with the lowest load flow;
    c) If this lowest load flow is smaller than a threshold, for example 0.1p.u., then go to step d); otherwise stop searching for the similar hour and perform the risk assessment for this condition;
    d) Assume that the topology of the next hour does not have the branch found in b), then use the method described in point 1 above to identify the similar hour.

The idea behind this method is that the presence or absence of very lightly loaded circuits has little effect on the risk assessment.

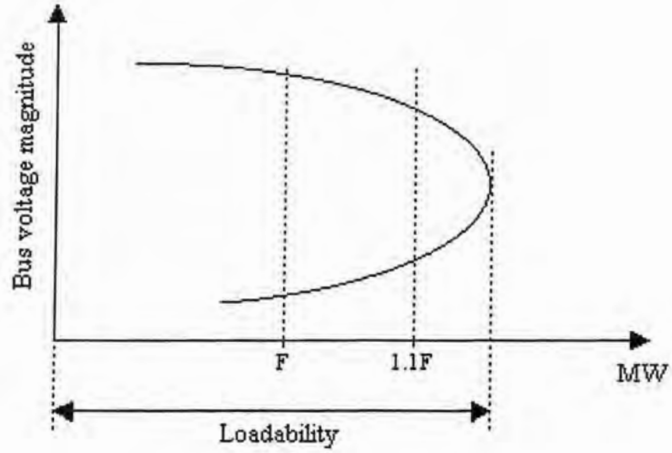
Implementing this speed enhancement, the number of hours need to be assessed can decrease drastically. For example, in the IEEE RTS'96 test system used in chapter 6, for one year of 8736 hours, it is only needed to assess the risk of 499 hours. Comparing all risk indices of the first hour and all of its similar hours (hour 2854, 3409, 3415, 3658, 4329, 5063, 8667, and 8670), the errors obtained are all below 2 %.

4.3.2 Increase the Speed of the Risk Calculation

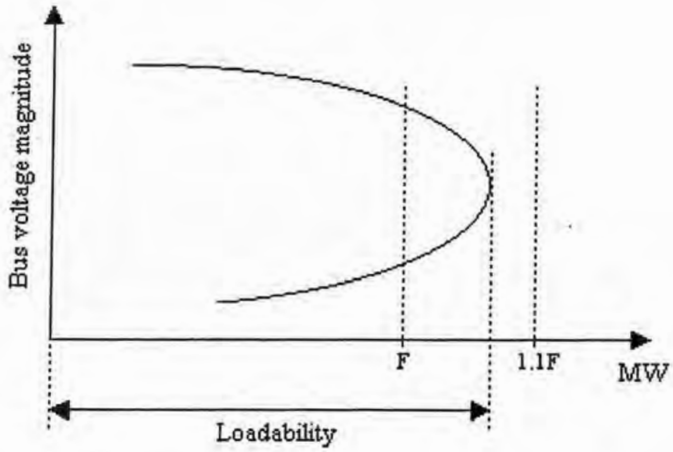
Risk calculation is a time-consuming procedure, especially when including the voltage instability risk calculation, as it requires the use of continuation power flow (CPF). However, the speed of the risk calculation can be improved in the following ways:

- *Contingency ranking*: The contingencies are ranked according to their loadability, which is used to quantify the voltage instability risk. The assessment proceeds down the ranking, from the most serious to less serious case, until a contingency results in zero voltage instability risk. For the contingencies less serious than this zero voltage instability risk contingency, the value zero is assigned to their voltage collapse risk without doing any further calculation.

- *Improved continuation power flow*: The index of loadability is used to quantify the voltage instability risk. In order to get the exact value of loadability, it uses the CPF, a very computation-intensive algorithm. But, if the system load level is much less than the loadability value, the system has no voltage instability risk at all. From the severity function presented in Figure 3.4, it can be seen that when the "%margin" is 10 % or more, the voltage instability severity is zero. Under this condition, there in no need to get the exact loadability value. So, in the CPF, first it is judged whether the system has 10 % or more; if yes, the value zero is assigned to the voltage instability risk of the system; if not, the CPF is used to get the exact loadability and thus the risk. Figure 4.2 illustrates this approach, where F represents the forecasted load in MW. Part a) shows a zero risk situation (the algorithm converges when evaluating for 10 % margin, which means that there is no need to determine the loadability value). The case illustrated in part b) has non zero voltage instability risk (the algorithm does not converge when evaluating for 10 % margin, which means that it is required to find the exact loadability value).



a) Voltage instability risk is zero



b) Voltage instability risk is non-zero

Figure 4.2 – Implementation of the improved continuation power flow

CHAPTER 5. UNIT COMMITMENT ADJUSTMENTS

5.1 OBJECTIVE

As mentioned in section 1.2, the purpose of this work is to develop a method to identify the relation between the unit commitment strategy and risk variation. Furthermore, the ability to suggest the adequate adjustments to implement in the unit commitment, in order to reduce the risk incurred by the system, is also part of the objective. To accomplish this, the risk-based assessment concepts described in chapter 3 and the long-term sequential simulation addressed in chapter 4 will be used.

After obtaining the results from the unit commitment following the procedure described in section 2.3.3, the annual risk assessment is performed. The composite risk that the system incurs in each hour, taking into account all the contingencies considered and their probabilities, is then evaluated. The basic idea is that through the inspection of the composite risk curve for the year, the unit commitment transitions (especially shut-down transitions) that cause significant risk increase can be identified. After identifying these unit commitment transitions, the unit commitment program is rerun with the identified units that have undesirable effects on risk constrained "on". These changes in the unit commitment will have a corresponding change in cost and in risk. The decision to accept or reject each change in the unit commitment will then depend upon the compromise between these two effects, and this decision is to be taken after each modification. The complete procedure for a single update in the unit commitment is illustrated in Figure 5.1.

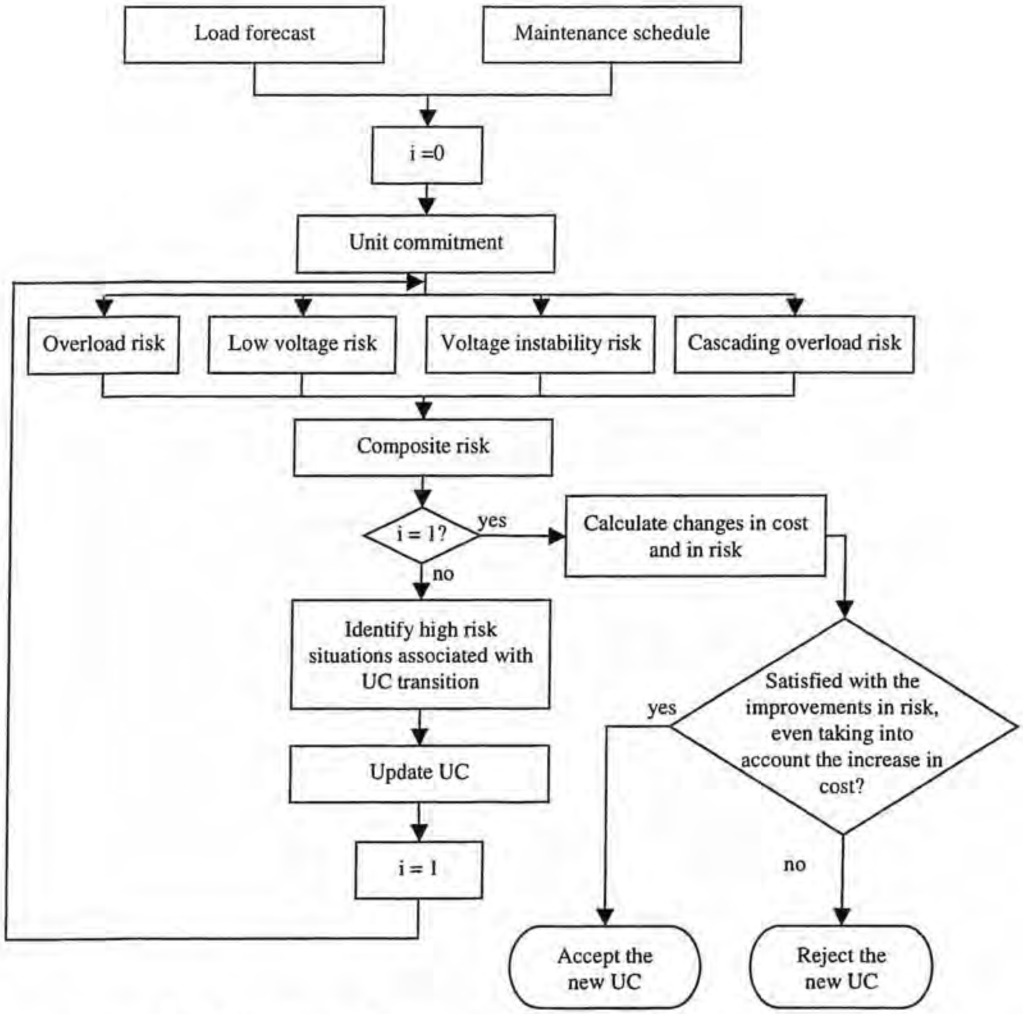


Figure 5.1 – Flowchart of the procedure for a single change in the unit commitment

The constraints imposed into the unit commitment are designed to accomplish a good compromise among the following three different objectives:

- Maximize risk decrease of high-risk hour;
- Maximize cumulative risk decrease;
- Minimize cost increase.

Our approach addresses this multi-objective optimization problem by solving two separate problems. One deals simply with the first objective presented above and the other one takes care of the remaining two objectives by introducing the concept of cumulative risk-cost ratio.

The methodology is based on some assumptions that are addressed in section 5.2. The details of the algorithm are presented in section 5.3.

Note that there is no single optimal solution, as it depends on the amount of risk that the decision-maker is willing to take, in relation to the amount of money the decision-maker is able to save or to make. Therefore, this approach does not aim to identify the optimal solution, but rather to illuminate the differences between the risk levels and operating costs of various alternatives. To do this, one unit commitment change is performed at a time, followed by the evaluation of the corresponding modifications.

5.2 ASSUMPTIONS

As mentioned before, each update in the unit commitment will be defined after solving two problems: one in which the objective is to maximize the risk decrease of the high-risk time period and another in which the objective is to simultaneously maximize cumulative risk decrease and minimize cumulative cost increase. The solution algorithm is based on assumptions that are described on the next two subsections, according to the problem to which they apply.

5.2.1 Maximize Risk Decrease of High-Risk Hour

In order to maximize the risk reduction of the high-risk time period, the largest risk decrease is assumed to occur from constraining units to be "on", in contrast to constrain units to be "off". This is a very intuitive assumption, since imposing units to be "on" increases the generation capacity, the inertia of the system, and the versatility to operate it, thus contributing to a situation where security levels are expected to improve.

The other assumption is that the highest risk decrease occurs from constraints imposed on units that are "off" during all or part of the high-risk time period. This includes units that are shut down outside the high-risk period but go back up within the high-risk period. As a result of this assumption, the constraints introduced will certainly include part or the entire high-risk time period, together with other possible time intervals. The idea is that at least part of the high-risk time period should be included in order to maximize risk decrease of high-risk hours.

The minimum down time and the minimum up time constraints associated to the thermal units make the unit commitment have, in general, an inter-temporal dependency characteristic. However, it is unlikely to obtain a fairly different solution at the high-risk hour due to a constraint imposed far back in time. In fact, a constraint imposed outside the high-risk time period can possibly have influence on the hours after which the constraint is valid, but this effect tends to vanish and the solution tends to return to the original schedule, as soon as the minimum down time and the minimum up time constraints are all satisfied. Note that imposing a unit to be "on" during a certain time interval can only affect other units in one way: making one or more units to be turned off during that time interval. But even if this happens, the only way that this/these change(s) can propagate outside that time period is if this/these other unit(s) need to remain "off" to satisfy the minimum down time constraint. However, as soon as this constraint is verified, the solution will return to the original schedule, since it corresponds to the economic optimum.

On the other hand, if this assumption was not to be considered, all the possible combinations of units up/down that occur before the high-risk time period would have to be examined, which would define a real practical barrier in the problem related to the high dimensionality of the possible solution space.

Furthermore, it is intended to minimize perturbations in the original unit commitment schedule, since it corresponds to the most economic solution. Note that, as mentioned in the previous section, another objective that must be taken into account when incorporating new constraints into the problem is that the cost increase has to be minimized.

5.2.2 Maximize Cumulative Risk Decrease and Minimize Cost Increase

Among all the possible constraints that impose a unit to be "on" during at least part of the high-risk time period, the most effective one will be identified based on the cumulative risk-cost ratio. This ratio is defined as:

$$\frac{Cumulative\,RiskDecrease}{Cumulative\,CostIncrease},$$

and larger values of this ratio are more desirable than smaller values. The assumption presented in the previous section implies that the constraint imposed will include the high-risk time period. If previous intervals where the unit is "off" are also considered for reversal, together with the time interval that includes the high-risk situation, it can happen that the cumulative risk-cost ratio becomes larger than the obtained with only one constraint (again, the one that includes the high-risk situation). So, the idea is to verify how the risk-cost ratio evolutes with the incorporation of more time intervals and select the option that as associates the greatest value for this ratio.

Let us consider the unit commitment schedule for unit X presented in Table 5.1, where "1" means that the unit is "on" and "0" means that the unit is "off".

Table 5.1 – Example of a unit commitment schedule

Hour	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Unit X	0	0	1	1	1	1	0	0	1	1	1	0	0	1	1	0	0	0	0	1

Let us also consider that the cumulative risk for the original unit commitment solution follows the curve presented on the left in Figure 5.2. Hour 17 is the high-risk hour.

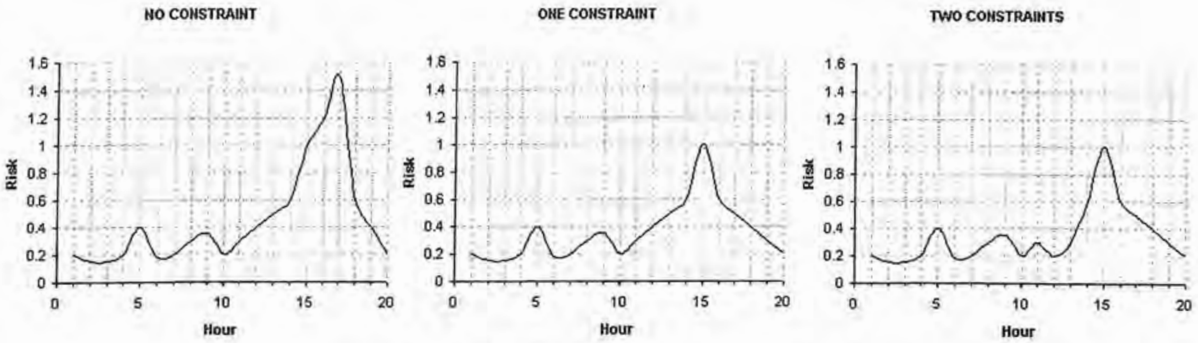


Figure 5.2 – Risk evolution with time

According to the assumptions presented in the previous section, the constraint imposed to unit X will certainly force the unit to be "on" between hour 16 and hour 19 (the time interval that includes the high-risk time period). After applying this constraint, the cumulative risk obtained is the one depicted in the central part of Figure 5.2. As expected, the cumulative risk decreased between hour 16 and hour 19. This constraint also has a corresponding cumulative cost increase. The cumulative risk-cost ratio is A.

Considering also the next time interval for reversal (in this case, the period between hour 12 and hour 13) the cumulative risk curve obtained is presented on the right in Figure 5.2. As we can see, the risk decreased between hour 12 and hour 13 and also between hour 16 and hour 19. This solution has a corresponding cost increase resulting in a cumulative risk-cost ratio B.

If $B < A$, the constraint that is applicable only during the time interval between hour 16 and hour 19 is considered to be the best one to apply at unit X. Otherwise, we should continue going back in time including the next possible time interval until the cumulative risk-cost ratio starts falling. The risk-cost ratio is then assumed to be monotonically increasing with the number of intervals considered to constrain, until a point where this ratio is less than the one computed in the previous iteration. When this happens, the time intervals associated to the previous iteration are selected.

This assumption is based on the fact that, for a constraint imposed before but close in time to the high-risk situation, an increase in the risk-cost ratio can still be experienced, since the cumulative risk decrease typically dominates the cost increase, due to the proximity to the referred high-risk hour. This proximity will cause influences in risk levels that could still be significantly high. Therefore, the cumulative risk decrease can be very high. On the other hand, as we go back in time taking into account more time intervals, the operating cost will increase but the star up cost will most likely decrease. Note that, for the unit where the constraint is applied, there are as many star up costs eliminated as time intervals considered, since each constraint will prevent the unit to be turned off during a certain time interval. However, since the ratio starts decreasing as we consider time intervals that are far and far in time to the high-risk situation, it is assumed that it will no longer increase again, since the cumulative risk decrease is considered to grow less relatively to the cost increase, making the ratio diminish.

5.3 ALGORITHM

The following procedure is used to identify risk-based updates in the unit commitment solution:

1. *Identify hours for which risk exceeds the high-risk threshold.*
   These hours where the composite risk assumes large values indicate situations to investigate possible changes in the unit commitment solution, in order to improve the referred high-risk conditions. The high-risk threshold has been chosen to be 1.5. The next steps are taken to each high risk condition.

2. *Check the sensitivities of the high-risk situation.*
   Chances are that the high-risk problem can be fixed by another less expensive means than a unit commitment reconfiguration, such as generator terminal voltage control

for low voltage or voltage instability problems, or re-dispatch for overloads cases. To clarify this issue, the following sensitivities are computed:

$$\frac{\partial Risk}{\partial V_i} \quad i = 1, \ldots, N_g$$

$$\frac{\partial Risk}{\partial P_i} \quad i = 1, \ldots, N_g$$

$$\frac{\partial Risk}{\partial Q_i} \quad i = 1, \ldots, N$$

where V_i is the bus voltage, and P_i and Q_i are the real and reactive power injections, respectively, at bus *i*. *N* is the total number of buses and N_g is the number of buses connected to generators.

If the sensitivities with respect to the voltage or the real power injection are high for a committed unit, and if that unit has control capacity remaining, the high-risk time period is improved making use of this capacity. If the sensitivity with respect to the reactive power injection is high for a load bus with shunt capacitors available, the high-risk situation is improved using this facility. But if any of the sensitivities computed is high for a decommitted unit, then this suggests that a unit commitment modification should be made.

The following steps apply if a unit commitment adjustment is to be made, i.e., if there is no less expensive alternative to improve the high-risk situations or if this/these alternative(s) are not enough to get the desired risk levels.

3. *Identify all the unit commitment transitions that occurred before that hour.*

   At this step in the algorithm, all unit commitment transitions occurring before the high-risk hour should be considered as possible contributors to the risk level of the high-risk hour, thus becoming candidate transition reversals for accomplishing the objective.

4. *Eliminate the nonreversible transitions.*

   Under the assumptions used in this study, the nonreversible transitions are those that occur in nuclear and hydro units, because nuclear shut down transitions are made only for maintenance, and hydro shut down transitions are made only because there is insufficient hydro energy. These assumptions may be lifted if desired. As a consequence, in this research work, the transitions that should be considered are those that occur only for economic reasons, and will include only shut down transitions for thermal units.

5. *Select the candidate transitions.*

   Among all shut down transitions occurring in thermal units previous to the high-risk period, the *candidate transitions* are selected. These are the transitions that will be considered for reversal. Cost is used as the criteria for selecting these candidate transitions; the transitions occurring for the lowest cost units are selected. This criterion may be implemented in a number of ways. In our approach, the cost is evaluated based on full-load average production cost, FLAPC (this cost is given by the net heat rate at full load multiplied by the fuel cost) and the transitions selected are those occurring for units having FLAPC within x % of the FLAPC for the next least costly unit. Here, x is chosen to be 20 %.

6. *Reverse the candidate transitions.*

   Each of the candidate transitions are reversed, one at a time, in order of their temporal proximity to the high-risk hour identified in step 1. This is done by constraining the identified units to be "on" (one unit at a time) during the corresponding identified time period and rerunning the unit commitment program.

7. *Evaluate the risk decrease for the high-risk hour.*

   For each of the unit commitment adjustments performed in the previous step, the decrease in risk for the high-risk hour is computed. The adjustment will only be accepted if it decreases the risk for the high-risk hour to an acceptable level, within the threshold. This level is assumed to be 1.5.

8. *Compute the changes in risk and the changes in cost.*

   For each of the unit commitment adjustments that satisfy the risk threshold condition specified in the previous step, the decrease in risk and the increase in cost are evaluated. The decrease in risk is obtained by repeating the simulations to perform the risk assessment. The increase in cost is calculated knowing the new generation outputs, the incremental cost rates, and the star up costs.

9. *Identify the effective transition.*

   The effective transition will be selected for having associated the maximum value of the cumulative risk-cost ratio.

CHAPTER 6. THE COMPETITIVE MARKET ENVIRONMENT

6.1 RESTRUCTURED POWER INDUSTRY STRUCTURE

In a traditionally organized electric power industry, the transmission system and multiple generation units are owned by the same company, which operates them together and controls the costs. However, with the intention to bring about competition in some of the electricity business activities, as well as to promote a higher level of efficiency in the provision of electric services, the power system has been shifting from a deterministic regulated system to a competitive and uncertain market environment. This profound restructuring process in the electricity industry is on effect in an increasing number of countries. Although the details of the deregulated marketplace may vary from one case to another, it is generally assumed that electricity should be traded in a similar fashion to other energy commodities.

In the United States, the Federal Energy Regulatory Commission[1] (FERC) began regulatory reform of transmission in 1996, with the objective of encouraging competitive regional electricity markets that promote economic efficiency without compromising system reliability. The regulatory approach, embodied in a series of orders, has been to provide an open market architecture where alternative market designs are implemented, evaluated, and changed when necessary. Orders 888 [41] and 889 [42] were issued by FERC in 1996. These orders required an open access transmission regime, based on non-discriminatory transmission rates and transparent posting of available transmission capacity. Order 888 also

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[1] The Federal Energy Regulatory Commission (FERC) was created through the Department of Energy Organization Act on October 1, 1977. FERC's mission is to promote dependable, affordable, and competitive markets, supporting a strong and stable economy. Among other responsibilities, this independent regulatory agency regulates the transmission and wholesale sales of electricity in interstate commerce. More information about FERC is available at http://www.ferc.gov.

included fairly broad organizational principles for an Independent System Operator (ISO), an institution that separates ownership from control of the grid and can perform market functions. The ISO is responsible for physically controlling the system to maintain its security and reliability. Some implementation today are lacking in a financial objective for the ISO. The work reported in this thesis would assume the ISO has such an incentive.

By early 1999, a certain amount of inertia was evident in the development of wholesale markets. Electricity traders expressed dissatisfaction with the traditional methods of transmission grid management still employed in large parts of the United States. Specifically, there was substantial concern about frequent curtailments of transactions, justified on the basis of reliability but often questioned by parties to the transactions [43]. Such curtailments are supposed to follow the North American Electricity Reliability Council's[1] (NERC) procedures, which provide criteria for the management of congested transmission facilities.

On December 15, 1999, FERC took a step toward clarifying the appropriate transmission access and market institutions with Order 2000 [44], which requires the formation of regional transmission organizations (RTO). The order establishes in the RTO many of the features that had emerged in the ISO markets as well as additional characteristics and functions that address unresolved issues in both ISO and non-ISO electricity markets. The RTO is required to serve a region of sufficient scope and configuration to provide for a reliable, efficient electricity market.

In this restructured industry, the electric energy is produced by generating companies (GENCO), sold to energy service companies (ESCO), and delivered through facilities owned

[1] The North American Electric Reliability Council (NERC) is a non-profit corporation formed in 1968. Since then, NERC promotes electric system reliability and security by, among other responsibilities, establishing operating and planning standards. On October 16, 2001, NERC's Board of Trustees directed NERC to take all necessary steps to become the single organization in North America to develop both electric reliability standards and wholesale business practice standards, and to file such standards with FERC and appropriate government agencies in Canada. More information about NERC is available at http://www.nerc.com.

by transmission companies (TRANSCO) and distribution companies (DISCO). An entity such as NERC sets the reliability standards. The contract prices are discovered in an auction, where buyers and sellers of electricity make bids and offers that are matched. An ISO or RTO implements the results of the bidding process to create a full schedule of system operation that meets regulatory reliability and security requirements.

The entities such as GENCOs, ESCOs, TRANSCOs, and DISCOs represent market participants that operate now in a competitive fashion, with the objective of maximizing their profits.

6.2 UNIT COMMITMENT PROBLEM IN A DEREGULATED MARKET

When defining the unit commitment problem solution in the traditionally organized electric power industries, the main source of uncertainty is the load. Once the load is specified, the generator cost curves may be utilized to identify the minimum cost unit commitment and dispatch, in order to have enough capacity to supply the electricity demanded by the utility's customers. However, in competitive electric energy systems, the load uncertainty remains, but generator cost curves may not be available to utilize in a unit commitment program, and so there is additional uncertainty regarding the valuation of generation from one unit relative to another.

In general, in a competitive electric energy system, the unit commitment and dispatch are specified according to the price discovery made in one of the following two ways:

- *Contracts*: Bilateral or multilateral contracts may be signed between sellers and buyers for a specified length of time, the contract duration. Such contracts fix the amount of load to be supplied by each seller for the contract duration. If the seller owns only a single unit, then the unit commitment and dispatch is also fixed for that unit. But if the seller owns multiple units, then the seller may utilize a traditional unit commitment program to determine the minimum cost solution. The resulting schedules are determined by each seller and submitted to the organization responsible for the security of the system (we assume this organization is an ISO). These schedules would then be utilized in the long-term simulation performed by the ISO.

- *Spot market*: The spot market is generally comprised of day-ahead and hour-ahead decision-making systems, with the day-ahead market determining unit commitment and the hour-ahead market determining dispatch. Such decision-making systems are generally auctions. Minimally, their inputs are sell-bids, but two-sided auctions may accept both sell and buy bids. Given that the auction structure and the bid selection algorithm are known, then this can be coded and interfaced with the long-term simulator described in chapter 4, in order to generate a unit commitment solution. However, the algorithm does require the daily and hourly bids. Thus, it is also necessary to develop a bid generation application in order to perform the long-term simulation. Different methods are available to do this [45].

6.3 APPLICATION OF OUR APPROACH

The approach described within this thesis detects and corrects unit commitment schedules that significantly contribute to high risk associated with overload, low voltages, voltage instability, and cascading overloads. This method is clearly useful for traditionally organized electric power industries that own and operate the transmission system together with multiple generation units, and the generation units are centrally scheduled to minimize production costs and meet demand. Yet, is this approach applicable to competitive electric energy systems where the owner/operator of generation and transmission are distinct, and where there exist multiple generation owners? This question is a relevant one because our approach depends on the ability to formulate meaningful future operating scenarios on which the risk assessment is performed.

As indicated in the previous sections, contracts are submitted to the ISO and spot markets may be simulated by the ISO in order to obtain meaningful future unit commitment schedules. Therefore, from the point of view of the ISO, the unit commitment problem continues to be applicable, and meaningful future operating scenarios, on which the risk assessment is performed, can be formulated (either under contracts or within the framework of a sport market). Furthermore, in most successful electricity markets, the long-term contracts assume the most significant expression of trading, while the spot market handles just a small percentage of it. This means that, in the majority of the cases, the exact unit commitment is known.

The ISO, as a non-profit organization, manages the transmission grid, controls the dispatch of generation, oversees the reliability of the system, and administers congestions protocols. Its economic objective is to maximize social welfare, which is obtained by minimizing the costs of reliably supplying the aggregate load. Furthermore, it is also assumed that it is the ISO who performs the long-term sequential simulation, risk assessment, and unit commitment adjustment. This means that the ISO has authority to reschedule the units, which is the case for most electricity markets that have been implemented.

In the next chapter, a traditionally organized electric power industry is adopted in order to illustrate the central technology (long-term simulation with risk assessment) within the given budget. However, it is possible to implement this approach for competitive electric energy systems if desired.

CHAPTER 7. SIMULATION RESULTS

7.1 TEST SYSTEM

In order to highlight the methodology described above, this chapter presents the results of a case study. The network used is the IEEE Reliability Test System'96 [46], shown in Figure 7.1.

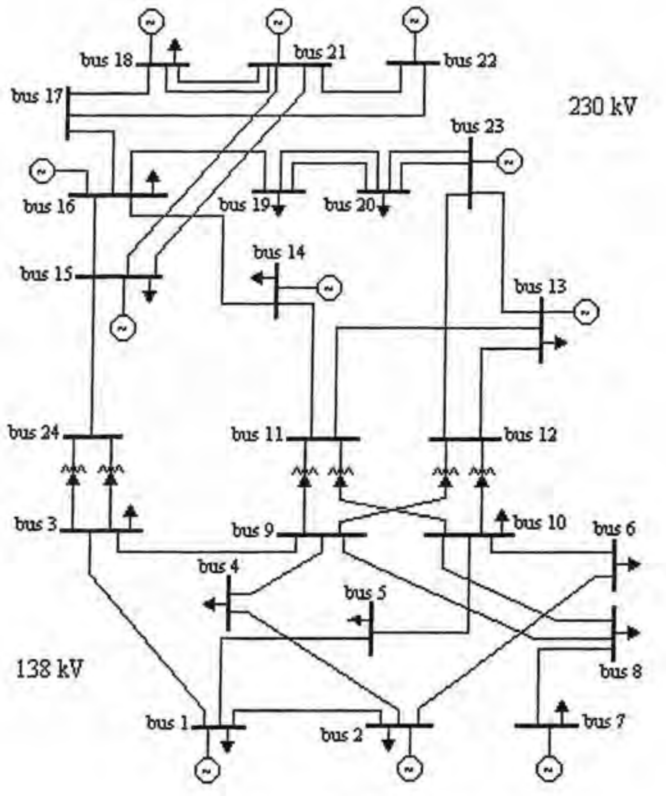

Figure 7.1 – The IEEE RTS'96

The IEEE RTS'96 consists of a 24-bus system with 17 buses loaded. It has 32 generator units (24 thermal units, 6 hydro units, and 2 nuclear units).

The load percentage data given in [46] is used as the expected load percentage at each bus. However, to stress the system and highlight the strength of risk assessment, the load was increased by 14 %. The expected hour-by-hour one-year loading trajectory used in the analysis is shown in Figure 7.2. Each bus' load, at each hour, is assumed to follow a Normal distribution about its forecasted value with a standard deviation of 10 % of its expected value.

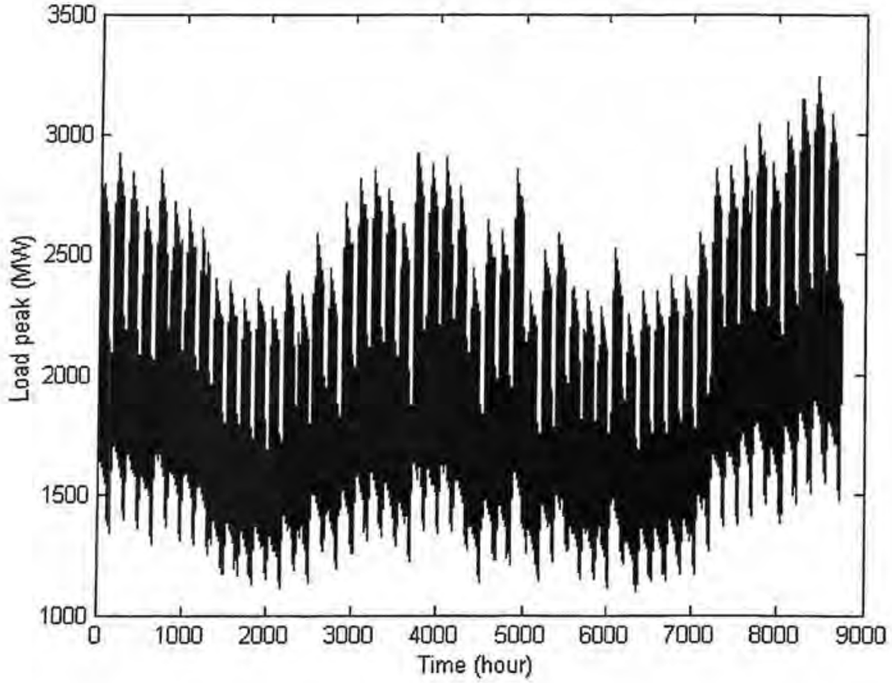

Figure 7.2 – Expected system load curve over one year

The procedure described before is illustrated in the following sections. Thus, section 7.2 presents the unit commitment solution for one year, accordingly to the heuristic algorithm developed in section 2.3.3. The annual risk assessment is then performed and the results presented in section 7.3. Finally, section 7.4 addresses the unit commitment adjustments and highlights the procedure described in section 5.3, assuming that a unit commitment adjustment is needed to improve the high-risk situation.

7.2 UNIT COMMITMENT

The unit commitment solution is obtained following the algorithm presented in section 2.3.3. The output of each different type of generators (thermal units, hydro units, and nuclear units) for the entire year is presented in Figure 7.3.

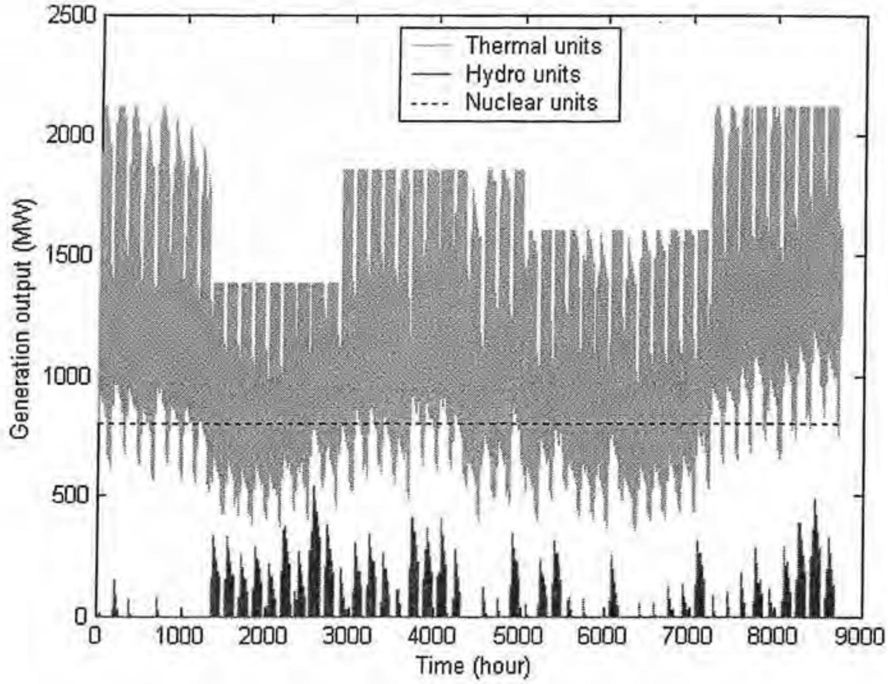

Figure 7.3 – Output of all the thermal units, all the hydro, and all the nuclear units

Among the thermal units, the economic dispatch was made based on the lambda-iteration method, considering the incremental fuel cost curves depicted in Figure 7.4.

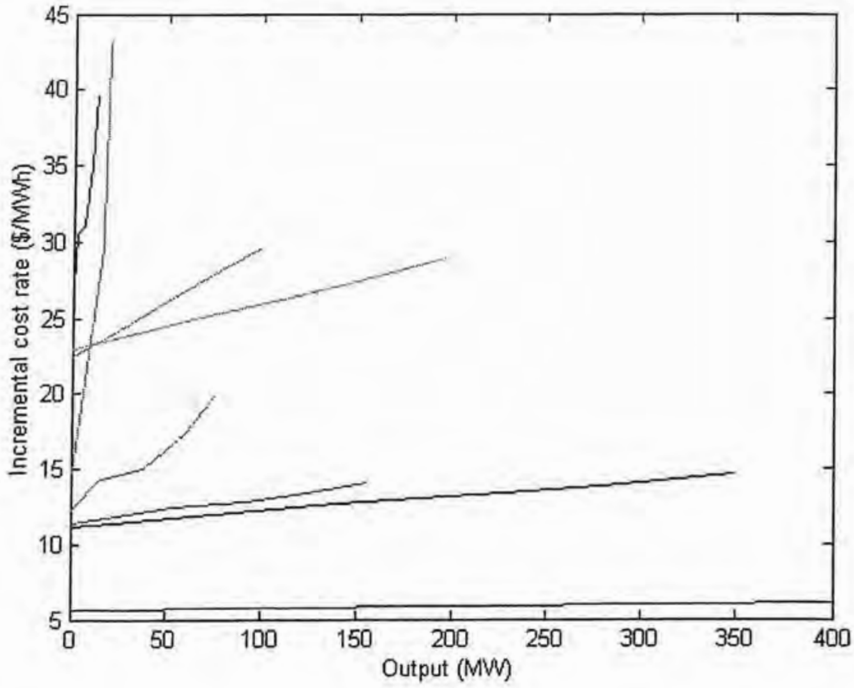

Figure 7.4 – Incremental fuel cost curves

These curves were obtained considering the incremental heat rates given in [46] and the following typical values: $3.0/MBtu, $1.5/MBtu, and $0.65/MBtu as the price for oil, coal and nuclear fuel respectively.

The full-load average production cost for each type of thermal units and the nuclear units is presented in Table 7.1.

Table 7.1 – Full-load average production cost

Unit Size (MW)	Unit Type	FLAPC ($/MWh)
12	Oil	39.657
20	Oil	43.281
76	Coal	19.966
100	Oil	29.631
155	Coal	14.072
197	Oil	28.860
350	Coal	14.652
400	Nuclear	6.1347

Figure 7.4 shows the value of the fuel cost per MWh, in each hour.

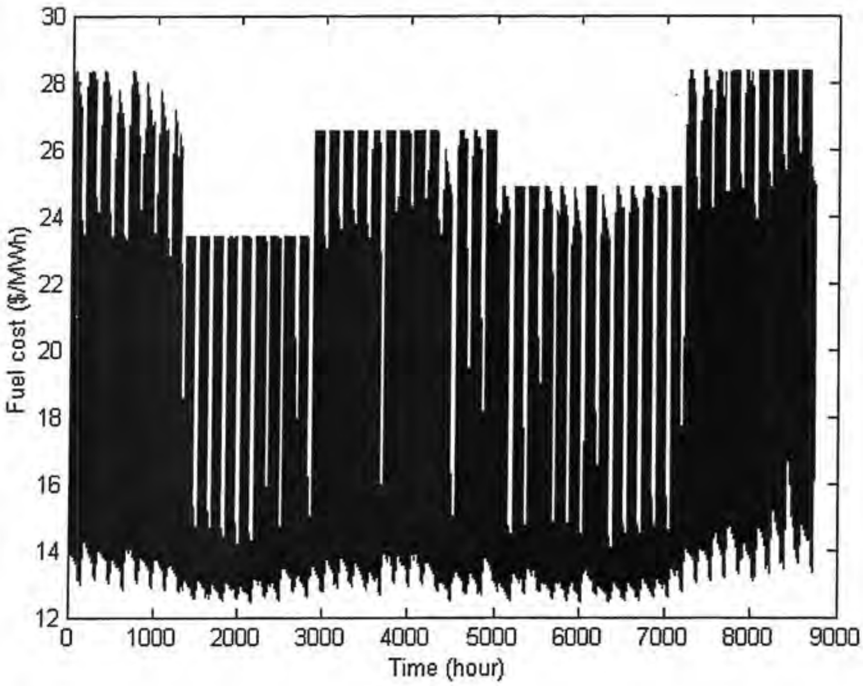

Figure 7.5 – Fuel cost per MWh

Combining this information with the generation results, one can obtain the total production cost including start up cost of the whole system, in each hour. This is presented in Figure 7.6.

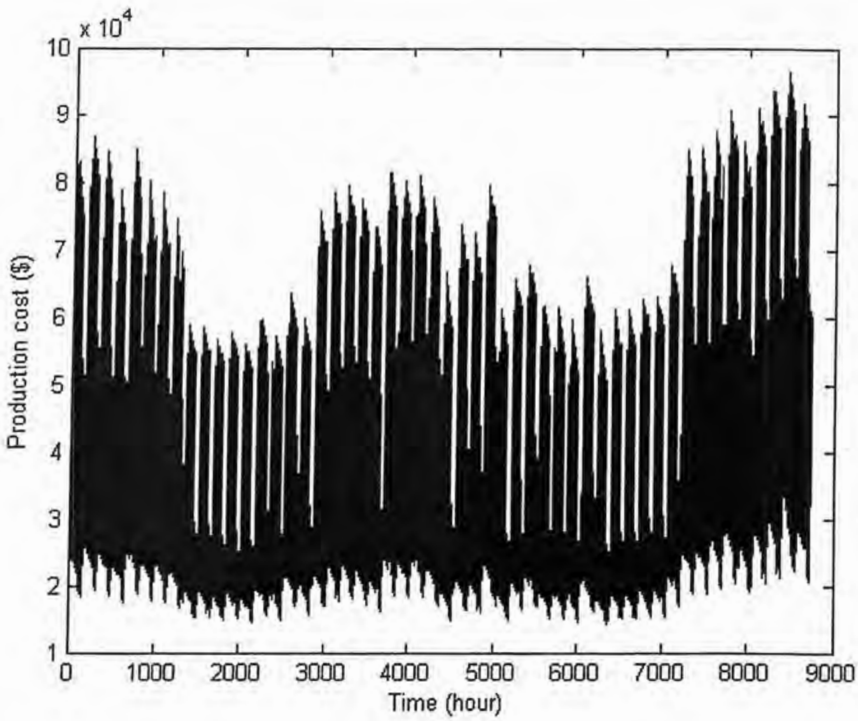

Figure 7.6 – Production cost

Finally, the total fuel cost of the system for the entire year is \$ 3.811×10^8.

7.3 RISK ASSESSMENT

Using the long-term sequential simulator, the overload, low voltage, voltage instability, and cascading overload risk of this system are computed. The time frame used for the simulation is one year. The contingency list used includes all N-1 contingencies of circuits and units (except the outage of line between buses 7 and 8, as it will cause the islanding of bus 7), and some N-2 contingencies, consisting of parallel lines. The results obtained taking into account all the contingencies considered and their probabilities are presented in the following four figures.

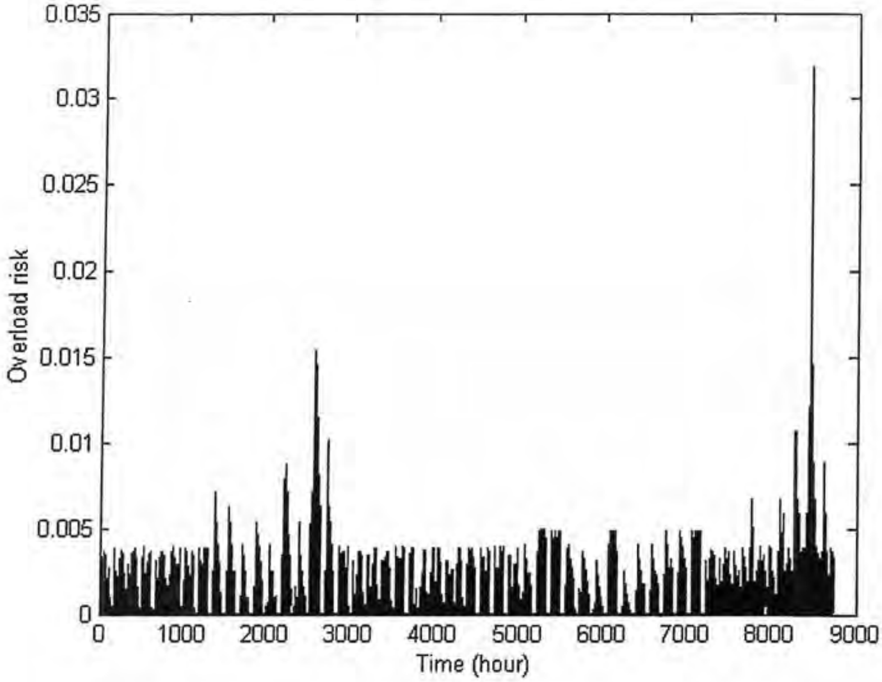

Figure 7.7 – Overload risk for the initial unit commitment

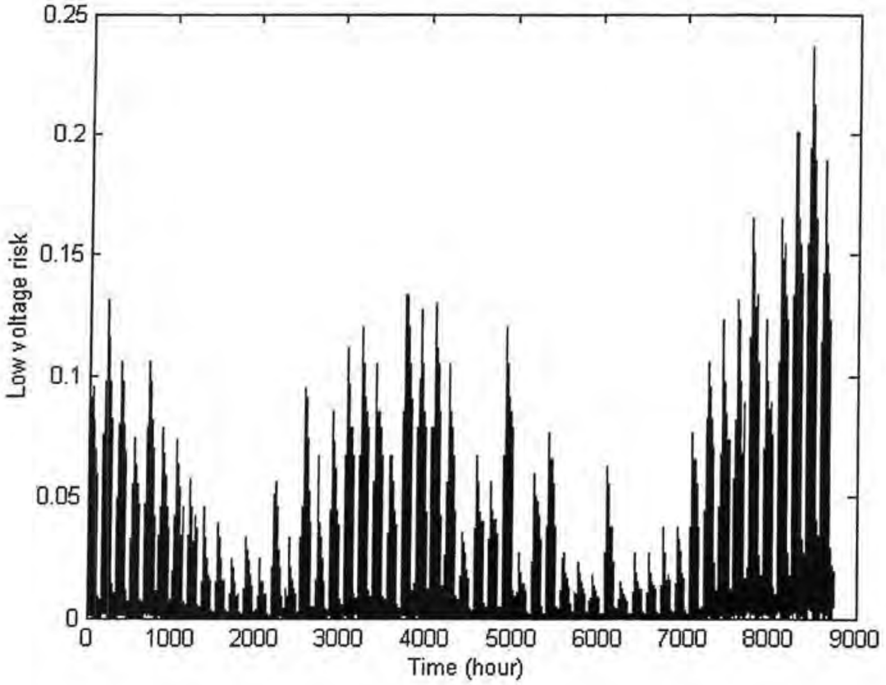

Figure 7.8 – Low voltage risk for the initial unit commitment

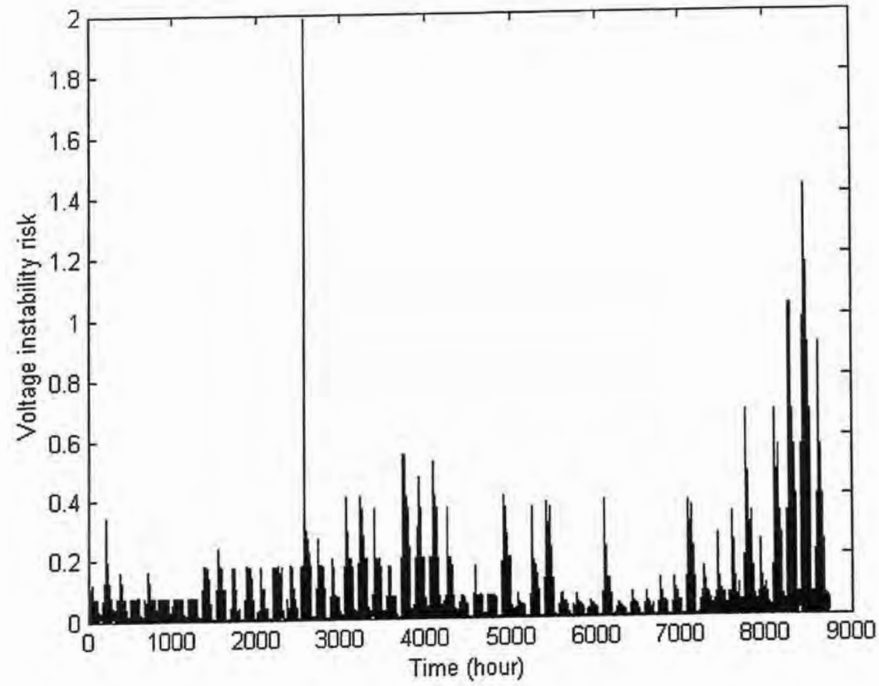

Figure 7.9 – Voltage instability risk for the initial unit commitment

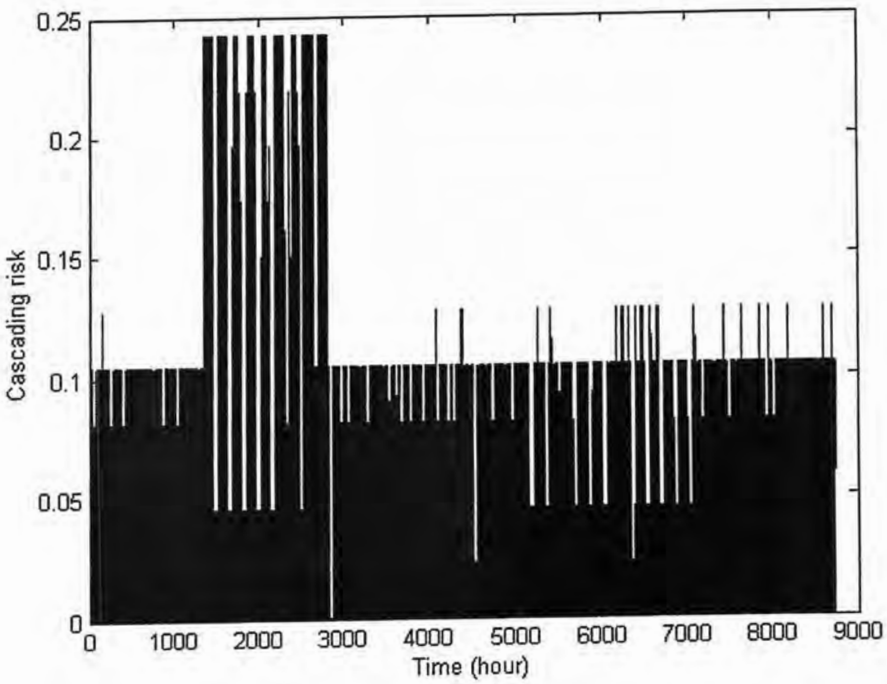

Figure 7.10 – Cascading risk for the initial unit commitment

The composite risk, which is simply the sum of the four kinds of risk considered, is depicted in Figure 7.11.

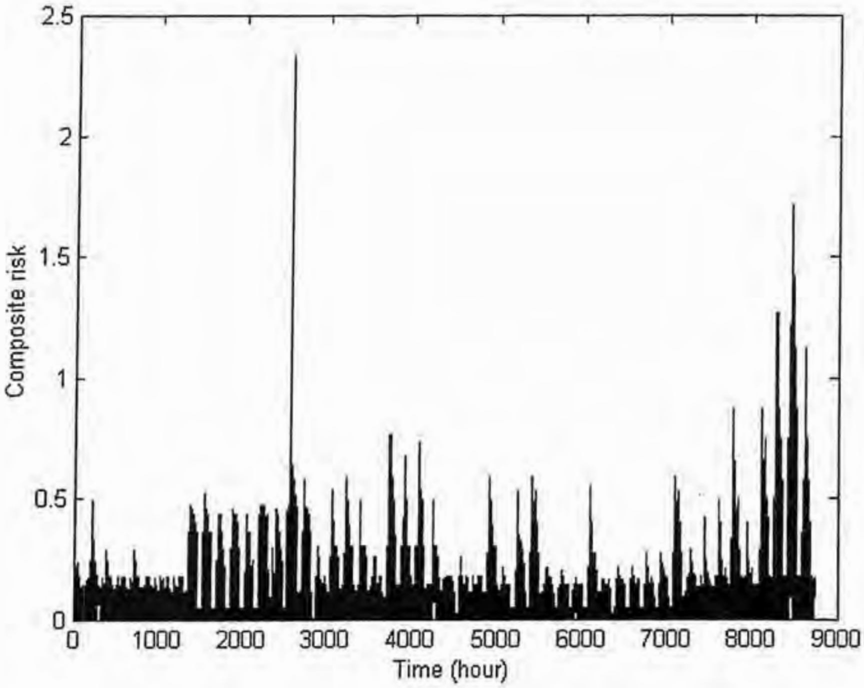

Figure 7.11 – Composite risk for the initial unit commitment

The peak risk occurs at hour 2555 and assumes the value 2.34. At this hour, the peak load is 2592 MW, which corresponds to 80 % of the annual peak load (3240 MW). The cumulative composite risk (summed over the whole year) is 893.80.

7.4 UNIT COMMITMENT ADJUSTMENTS

This section presents the results for the first iteration of the unit commitment adjustments, following the algorithm described in section 5.3 and assuming that a unit commitment adjustment is the best alternative to improve the high-risk situation.

The high-risk hour was identified to be hour 2555. At this time, the composite risk assumes the greatest value. This indicates that all the unit commitment transitions that occurred before that hour will be investigated, in order to identify the one that reversed has the most influence on the high risk situation.

As explained before, the unit commitment transitions in nuclear and hydro units are nonreversible, according to the way the unit commitment algorithm was defined itself. Therefore, the only transitions that will be considered are those occurring in thermal machines. Before hour 2555, the thermal units that experience unit commitment transitions are listed in Table 7.2.

Table 7.2 – Thermal generators with unit commitment transitions before hour 2555

Bus	Unit Size (MW)	Number of Units	FLAPC ($/MWh)
13	197	3	28.860
7	100	3	29.631
15	12	5	39.657
1	20	2	43.281
2	20	2	43.281

Among them, those with capacity 197 MW have associated the smallest full-load average production cost (28.860 $/MWh). The next ones in this rank are the thermal units with capacity 100 MW, with a full-load average production cost of 29.631 $/MWh. According to step 5 of the algorithm developed in section 5.3, since,

$$\frac{29.631-28.860}{28.860}=0.027<0.2 \qquad (7.1)$$

these thermal units will also be considered candidate machines to see their unit commitment reversed for some time period. The same does not happen to the others units listed in Table 7.2. In fact, we have:

$$\frac{39.657 - 29.631}{29.631} = 0.338 > 0.2 \qquad (7.2)$$

Therefore, the candidate transitions are all the shut down transitions occurring in thermal units with capacity 100 MW and 197 MW that happen before hour 2555. Table 7.3 presents the unit commitment transitions that occur in these machines, from hour 2463 to hour 2570, where "1" indicates that the generators are "on" and "0" indicates that they are "off".

Table 7.3 – Unit commitment transitions

Unit Size (MW)	Time Range (hour)							
	2463-2465	2466	2467-2469	2470-2527	2528-2542	2543-2551	2552-2567	2568-2570
100	1	0	0	1	0	1	0	1
197	1	1	0	1	0	1	0	1

Note that, at this time, step 5 of the algorithm developed in section 5.3 is completed. Steps 5, 6, 7, and 8 will be addressed separately for each type of generators selected. Section 7.4.1 describes these steps for the thermal units with capacity 197 MW, section 7.4.2 describes these steps for the other generators of 100 MW, and finally section 7.4.3 summarizes the results obtained during the computation of the first iteration of the unit commitment adjustments.

7.4.1 Analysis of the Units with Capacity 197 MW

As indicated in Table 7.3, the thermal units with capacity 197 MW are turned "off" between hour 2552 and hour 2567, which includes the highest risk situation. Thus, this is the first unit commitment transition reversed, according to step 6 of the algorithm presented in section 5.3. After performing this change, i.e., after imposing these units to be "on" during this time interval and rerunning the unit commitment program, the composite risk curve obtained is presented in Figure 7.12.

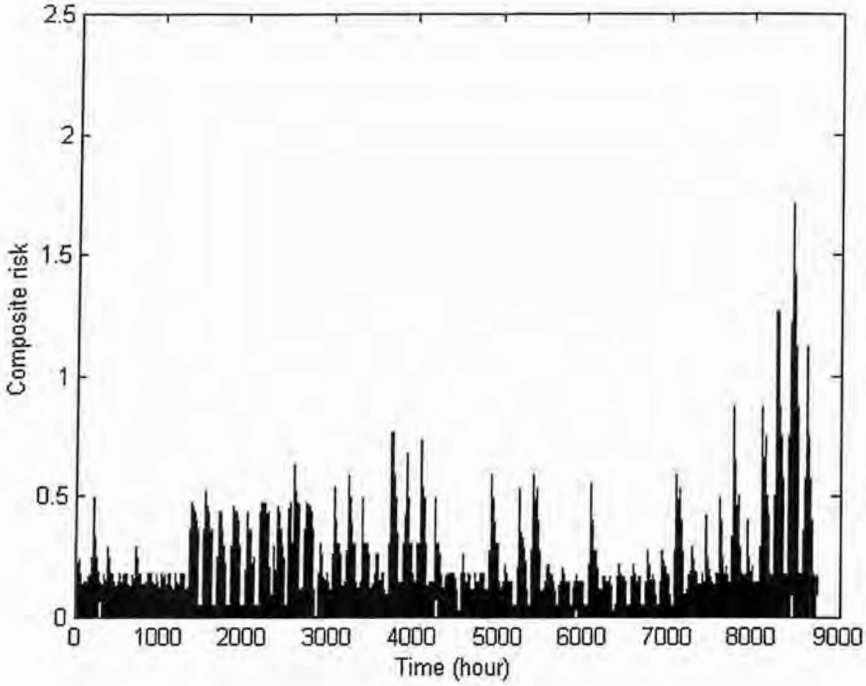

Figure 7.12 – Units of 197 MW constrained "on" during one time interval

At hour 2555, the composite risk is now 0.29, against the initial value of 2.34. Since 0.29 is less than 1.5,.this constraint satisfies the acceptable level defined in step 7.

The cumulative composite risk decreases from 893.80 to 884.13. On the other hand, the total production cost increases \$1,228.4. So, for this solution the cumulative risk-cost ratio is as follows:

$$\frac{Cumulative\ RiskDecrease}{Cumulative\ CostIncrease} = \frac{893.80 - 884.13}{1{,}228.4} = 0.0079 \qquad (7.3)$$

The next step performed corresponds to the update of the next candidate transition, going back in time. Table 7.3 shows that these machines were also turned "off" between hour 2528 and hour 2542. When the simulation proceeds constraining these thermal units to be "on" also during this time period, the composite risk curve obtained is depicted in Figure 7.13.

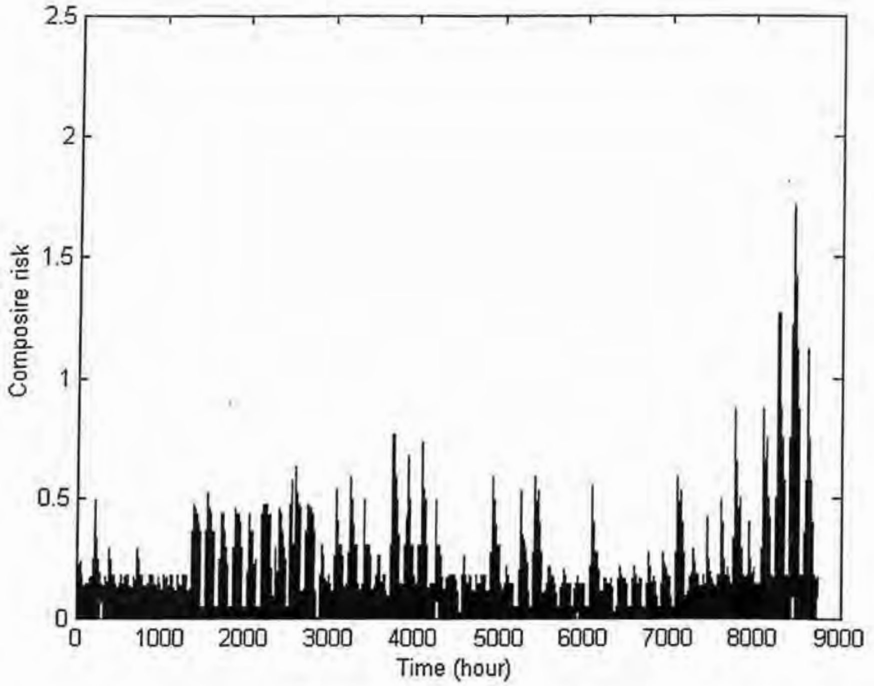

Figure 7.13 – Units of 197 MW constrained "on" during two time intervals

As it can be easily concluded by simply inspection of this figure, constraining the unit commitment for one more time interval does not have much influence on the risk curve. At hour 2555, the composite risk remains at 0.29, and the cumulative composite risk decreases to 883.78.

These results are in concordance with the assumption presented in section 5.2.1. In fact, imposing a constraint in the unit commitment from hour 2528 until hour 2542 did not have influence on the risk level at hour 2555. This new constraint introduced only a small reduction in the composite risk value, when comparing these results with those obtained previously, when there was only one constraint imposed to these unit, from hour 2552 until hour 2567.

Since from the original unit commitment solution there is now an increase in the production cost of \$2,381.5, it follows that:

$$\frac{Cumulative\ Risk Decrease}{Cumulative\ Cost Increase} = \frac{893.80 - 883.78}{2{,}381.5} = 0.0042 \qquad (7.4)$$

Because this cumulative risk-cost ratio is less than the one obtained for only one update in the unit commitment solution (see Equation 7.3), the algorithm does not continue testing candidate transitions for these units, according to the assumption presented in section 5.2.2. Instead, it is concluded that, for these thermal machines, the best unit commitment adjustment consists in constraining these generators to be "on" only between hour 2552 and hour 2567.

7.4.2 Analysis of the Units with Capacity 100 MW

Like the thermal units with capacity 197 MW, the generators considered in this section are also turned "off" between hour 2552 and hour 2567, which includes the highest risk situation. Thus, again, this is the first unit commitment transition reversed. Imposing the thermal units with capacity 100 MW to be "on" during this time period and rerunning the unit commitment program, the composite risk curve obtained is presented in Figure 7.14.

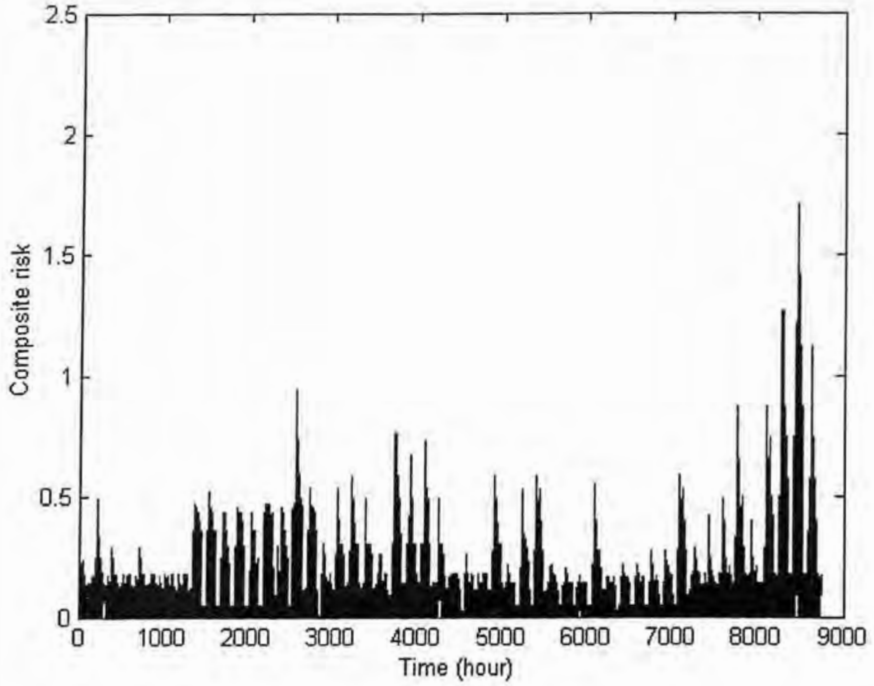

Figure 7.14 – Units of 100 MW constrained "on" during one time interval

At hour 2555, the composite risk is now 0.95, against the initial value of 2.34. One more time, since 0.95 is less than the acceptable level of 1.5, this constraint satisfies the condition for the risk decrease desired for the high-risk hour.

The cumulative composite risk decreases slightly from 893.80 to 892.62, while the total production cost increases $1,209.3. So, for this solution, the cumulative risk-cost ratio is:

$$\frac{Cumulative\,RiskDecrease}{Cumulative\,CostIncrease} = \frac{893.80 - 892.62}{1{,}209.3} = 0.0009 \qquad (7.5)$$

As it happened in the previous section, these machines were also turned "off" between hour 2528 and hour 2542. The composite risk curve obtained when they are also constrained "on" during this time period is depicted in Figure 7.15.

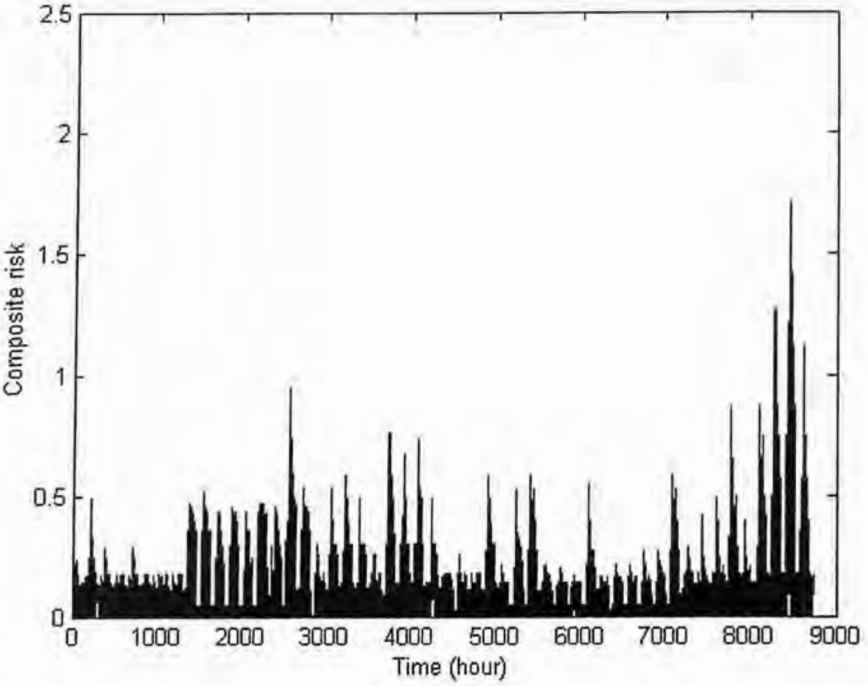

Figure 7.15 – Units of 100 MW constrained "on" during two time intervals

Again, there is not much change in the risk curve after imposing one more constrain in the unit commitment. The composite risk remains at 0.95 at hour 2555, and the cumulative composite risk decreases just to 890.69. From the original unit commitment solution the increase in production cost is now of $2,342.9. So, it follows that:

$$\frac{Cumulative\,RiskDecrease}{Cumulative\,CostIncrease} = \frac{893.80 - 890.69}{2{,}342.9} = 0.00133 \quad (7.6)$$

Since this cumulative risk-cost ratio is greater than the one obtained for only one update in the unit commitment solution (see Equation 7.5), the simulation continues reversing the next candidate transition. According to Table 7.3, the thermal units with capacity 100 MW were "off" between hour 2466 and hour 2469. Imposing them to be "on" also during this time period and rerunning the unit commitment program, the composite risk curve obtained is the one presented in Figure 7.16.

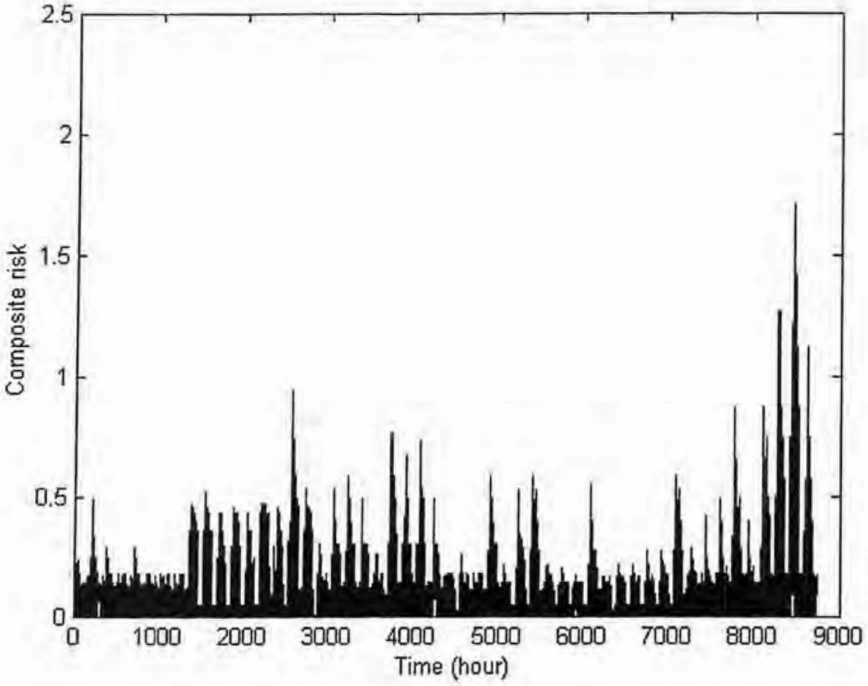

Figure 7.16 – Units of 100 MW constrained "on" during three time intervals

Again, the changes are not significant. At hour 2555, the composite risk is still 0.95. The composite cumulative risk is now 890.35 and the production cost increases $ 2,645.3. Thus, the cumulative risk-cost ratio is now:

$$\frac{Cumulative\,RiskDecrease}{Cumulative\,CostIncrease} = \frac{893.80 - 890.35}{2{,}645.3} = 0.00130 \quad (7.7)$$

Because this cumulative risk-cost ratio is less than the one obtained previously for two updates in the unit commitment solution (see Equation 7.6), the algorithm does not continue testing candidate transitions that are far back in time for these units. In conclusion, the best unit commitment adjustment for the thermal machines with capacity 100 MW consists in constraining them "on" during two time periods: between hour 2552 and hour 2567, and also between hour 2528 and hour 2542.

7.4.3 Solution of the First Iteration

According to step 9 of the algorithm developed in section 5.3, the best unit commitment adjustment in this first iteration consists in constraining the thermal units with capacity 197 MW to be "on" between hour 2552 and hour 2567.

Table 7.4 summarizes the results obtained while performing the first iteration of the unit commitment adjustments and highlights the selected solution.

Table 7.4 – Results obtained for the first iteration

	Changes in the 197 MW Units		**Changes in the 100 MW units**		
Time Period Constrained "On"	**2552-2567**	2552-2567 2528-2542	2552-2567	2552-2567 2528-2542	2552-2567 2528-2542 2466-2469
Decrease in Risk for the High-Risk Hour	**2.05**	2.05	1.39	1.39	1.39
Decrease in Cumulative Risk	**9.67**	10.02	1.19	3.12	3.45
Increase in Cost	**1,228.4**	2,381.5	1,209.3	2,342.9	2,645.3
Cumulative Risk-Cost Ratio	**0.0079**	0.0042	0.0009	0.00133	0.00130

CHAPTER 8. CONCLUSIONS

8.1 CONTRIBUTIONS OF THIS WORK

This thesis presents a method for identifying adjustments in long-term unit commitment solutions to reduce the risk associated with overload, low voltage, voltage instability, and cascading problems.

A heuristic approach, based on Lagrangian relaxation technique and priority list methods, is adopted to solve the referred problem. Besides overcoming the limitations of other methods related to the considered time frame, one very important advantage of this procedure lies in its ability to handle new constraints. In fact, this is a crucial issue, because the main idea of this work is the incorporation of new constraints into the unit commitment, as a result of the evaluation of the composite risk incurred by the system. These adjustments will most likely result in an increase of the generation cost. However, they will also translate an improvement on the annual risk.

The methodology proposed is not measuring risk violations for the worst contingency. Rather, it uses a measure of risk that accounts for all credible contingencies and their corresponding probabilities.

Furthermore, the risk assessment is directly referred to investigate which on/off transitions cause the high risky situations. If these two problems were to be incorporated together (the unit commitment and the risk assessment) in a unique stage, there were basically two possible approaches. One would be to balance the economic objective with the risk objective as a weighted multi-objective optimization problem. This would have the inherent difficulty of adjust the weights. Another, at least theoretical, possible approach would be to introduce a risk constraint directly into the unit commitment formulation. This risk constraint would specify a maximum limit for the composite risk, which should be verified. However, this way of solving the complete problem at once would demand an iterative process that would force repeated calculations of the risk value, which requires the main computational effort of the program. This could prevent a practical implementation. Furthermore, with this approach there would be no way of assessing the distance of an obtained solution from the optimal solution of the unit commitment without the risk constraint.

The validity of the solution methodology proposed, when applied to a traditional regulated electric industry, has been verified through the simulation results presented in the previous chapter.

8.2 SUGGESTIONS FOR FUTURE WORK

As suggested in section 3.2.1, risk indices may be used in economic decision-making problems. Therefore, a possible direction for future work is to define the monetary weight to assign to each component of the composite risk and integrate the objective of minimizing risk together with the objective of minimizing operation costs.

Profiling of the complete algorithm presented in this thesis indicates that the major computation time is allocated to the risk assessment module. In order to test large systems, a concurrent implementation may reveal not just convenient but also necessary, to increase computational efficiency. A concurrent implementation requires obtaining appropriate hardware and developing suitable code. The first condition is relatively simple today, as standard NT machines may be easily used. Modifying the code so that it is suitable for parallelization, though not conceptually difficult, will require some effort. However, since all the code is implemented in MATLAB language, one can take advantage of the existing multitask parallel processing toolbox that has been developed at Cornell University[1].

The unit commitment provides a basic foundation for effective bidding strategies. Therefore, this optimization problem will remain one of the central tools in the competitive electricity industry. In order to accurately model the actual competition environment, additional work needs to be done, as described in section 6.2.

[1] MATLAB is an interactive "matrix laboratory" for tasks involving matrices, graphics, and general numerical computation. The "Cornell Multitask Toolbox for MATLAB" enables multiple copies of MATLAB running simultaneously on a network of workstations to exchange matrices, thus facilitating parallel computations. More information regarding this toolbox is available at http://www.tc.cornell.edu/Services/Software/CMTM.

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